Vehicle classification based on images from visible light and thermal cameras

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Abstract

We propose novel vehicle detection and classification methods based on images from visible light and thermal cameras. These methods can be used in real-time smart surveillance systems. To classify vehicles by type, we extract the headlight and grill areas from the visible light and thermal images. We then extract texture characteristics from the images and use these as features for classifying different types of moving vehicles. We also extract several features from images obtained at night and during the day, which are the contrast, homogeneity, entropy, and energy. We validated our method experimentally and achieved that the accuracy of our visible image classifier was 92.7% and the accuracy of our thermal image classifier was 65.8% when vehicles were classified into six types such as SUV type, sedan type, RV type.

Keywords: Vehicle detection, Vehicle classification, Thermal camera, Entropy, Energy

1 Introduction

Recently, as vehicle traffic levels have increased, issues such as traffic accidents, congestion, and traffic-induced air pollution have arisen. Among these issues, traffic accidents present a particularly challenging problem. When conducting criminal investigations of traffic accidents, it is important to have automated ways of searching for suspicious vehicles. As a result, Intelligent Transportation Systems (ITS) have been implemented in many countries [1–3]. These systems detect and classify vehicles based on data from video and infrared cameras and acoustic and vibration sensors. However, the expense of traditional vehicle detection and classification systems renders them impractical. Furthermore, these systems are difficult to operate, as they require a large amount of hardware. Nevertheless, in the past decade, traffic surveillance cameras have been increasingly deployed to monitor traffic on major roadways. Hence, the effective utilization of these cameras for data collection is of practical significance.

One of the essential components of real-time smart surveillance systems in ITSs is that of moving vehicle detection and classification. Moving vehicles are detected from video frames by foreground extraction.

There is a range of vehicle detection methods, based on the inter-frame difference method [4], background extraction method, and optical flow estimation method [5]. Background subtraction is the first step toward object detection and can be performed using frame averaging, a single Gaussian [6], or a Gaussian mixture model (GMM). Friedman and Russel [7] proposed the basic idea of using a GMM for vehicle detection. They used three Gaussians to represent the road, shadow, and the moving vehicle. This method was then modified by Stauffer and Grimson [8], who used K Gaussians, where K was fixed. Zoran Zivkovic [9] used a Bayesian probability method to adaptively vary the number of Gaussian components required to model a pixel.

Hit-and-run is the act of causing to a traffic accident, such as colliding with another vehicle, and then failing to stop and identify oneself at the accident. Many hit-and-run accidents involving parked cars occur while the driver of the struck car is away from the car. Many studies have been devoted to the detection and classification of hit-and-run vehicles. However, relatively few studies have been conducted to identify the factors that contribute to the decision to run after a crash. There are many issues affecting the detection and classification of different types of vehicles. For example, it is important to classify a characteristic region rather than the contour of

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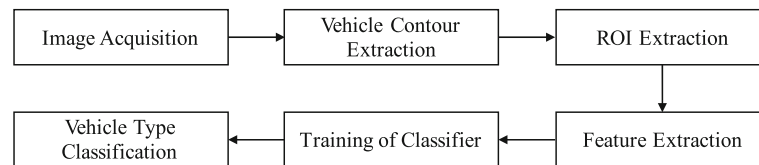
Fig. 1 Flow chart of a vehicle detection and classification system to facilitate traffic surveillance

a vehicle. However, image-processing techniques are very sensitive to variations in the external environment, so they tend to lose accuracy when the external environment changes rapidly.

2 Related work

Numerous researchers have proposed approaches for detecting vehicles and classifying different types of vehicles. In [10], standard Principal Component Analysis (PCA) was used for feature extraction, together with a nearest-neighbor classifier. However, as the evaluation database used in that study was relatively small, it is difficult to draw any firm conclusions from this work. In [11], a Haar wavelet was combined with Gabor features to describe the properties of a vehicle. Scale invariant feature transform (SIFT) features [12] were used in [13] to detect the rear images of vehicles. In [14], texture features were computed from frontal images of vehicles. The authors built a three-layer neural network and trained it with texture features. Thus, the neural network was able to recognize the make and model of moving vehicles.

In [15], a vehicle-detection and tracking system was developed to detect vehicles entering. This system measured optical flow and tracked vehicles by classifying their headlights, bonnet, front window, and roof area. In [16], the authors proposed a vehicle model recognition system based on a SIFT of an image of the vehicle's headlights and the homogeneity, which were calculated based on the distribution of features. In [17], license plates were extracted from ROIs and corner templates based on edge detection. In [18], a distortion invariant vehicle license plate and recognition algorithm were proposed based on a Difference of Gaussians (DoG) filter.

In addition, after geometric distortion correction and image enhancement, neural networks were used to recognize the license plates.

The authors of [19] presented a vehicle detection method based on extracting a histogram of oriented gradient (HOG) features from a given region of an image. In [20], a combination of speeded up robust features (SURF) [21] and edges was used to detect vehicles in the blind spot. Recently, researchers studying vehicle detection have moved away from complex image features such as Gabor filters and HOGs to simpler, more efficiently computable feature sets. As Haar-like features are sensitive to vertical, horizontal, and symmetric structures, and they can be computed efficiently, they are well suited to real-time vehicle detection applications [22].

In recent decades, traffic information was obtained using a thermal camera [23]. In addition, a thermal camera with UAV was used to detect objects in the ocean surface [24]. In [25, 26], people were detected and classified by a moving thermal infrared camera with the low-resolution images. In this paper, we propose a smart surveillance system to detect and classify vehicles during the day and at night. To achieve this, we first select regions of interest (ROIs) of the vehicle from the visible light and thermal images. Then, we measure the texture, contrast, homogeneity, entropy, and energy of the vehicle. We also estimate the aspect ratio of the headlight area and the grill area in each frame.

3 Method

3.1 System architecture

Figure 1 shows a flow chart of the vehicle detection and classification process. The vehicle detection and

a Raw data   **b** Foreground extraction
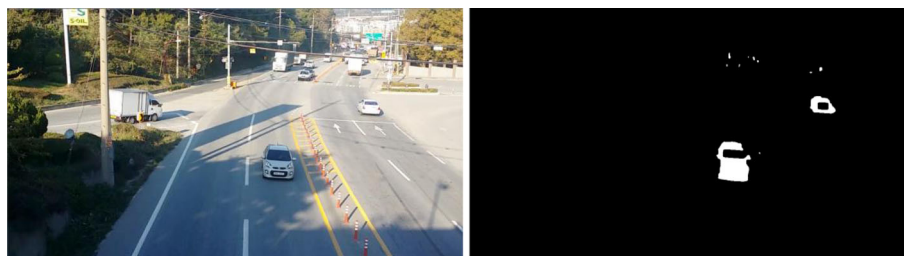
Fig. 2 Raw data and foreground extraction. **a** Raw data. **b** Foreground extraction

Fig. 3 Moving vehicle detected from the obtained images

First, a reference image is produced based on the initial images. Then, we compare the current image to the reference image to identify the foreground. The reference image can be produced by averaging the initial background images. The first step is to detect the vehicles that we will then classify. We detect the vehicles using the background modeling and subtraction (BGS) model. To make a robust, accurate model that can classify vehicles in real time, we also perform Gaussian background subtraction and filtering using functions provided by the OpenCV library [27]. We use pixel-based and non-motion-based background update methods to perform adaptive region-level background learning and updating. We exclude distant regions by specifying an ROI for each camera. To eliminate objects that are too small or too large, we use adaptive filters to calculate the object size and average vehicle height.

Figure 2 shows the obtained images and the results of the object subtraction step. As shown in the figure, when objects move through the image for a specified period, we update the motion history by comparing the current image to the first two images of the vehicle. We store the location of the center and direction of the object in a buffer. The center of the object in the next frame is determined as the point of the shortest distance between the center of the object in the previous frame and the center of the object in the next frame. Figure 3 shows the results of the foreground extraction step.

classification steps outlined in the flow chart are followed by both the visual and thermal image classification systems. The first step is to subtract the foreground image from a corresponding reference background image and decompose the image into regions that correspond to objects. In the second step, we extract the headlight and grill areas. In the feature extraction step, we extract object features such as the color, texture, and shape. The fourth step is to compare the features of different objects, either to identify them or to train the classifier. Finally, we classify the type of vehicle.

3.2 Foreground subtraction and ROI extraction of visual images
Foreground subtraction is a general method used to separate foreground objects from the rest of an image.

3.3 Feature extraction of visual images
In the feature extraction step, we detect Sobel edges in the ROIs of two consecutive images and measure vertical and horizontal projections in the grill and headlight regions. Figure 4a, b show the extracted edge image and horizontal projection of the ROIs, respectively. The grill and headlight regions are extracted using vertical projections and a median filter.

a Sobel edge image   **b** horizontal projection

Fig. 4 Sobel edge image and horizontal projection extracted from the detected vehicle as shown in Fig. 3. **a** Sobel edge image. **b** Horizontal projection

Fig. 5 ROIs extracted from the detected vehicle as shown in Fig. 3

In Fig. 5, the ROIs extracted from the detected vehicle are marked with red.

In general, vehicle models are identified using texture descriptors. Texture descriptors [28, 29] have been widely used to quantify the texture of objects. The differences between the brightness of the pixels represent the texture of the image. The local binary pattern (LBP) approach is a computationally simple method that provides highly discriminative texture information [30, 31] that is invariant to monotonic changes in gray level. We used histograms of LBP patterns as texture descriptors and classified them using a log-likelihood dissimilarity measure. The LBP operator was extended to utilize neighborhoods of different sizes [32].

We quantified textures by generating a gray level concurrence matrix (GLCM) based on the spatial relationships between pixels. The GLCM considers the relationship between two pixels at a time. These are denoted the reference pixel and the neighbor pixel. The GLCM matrix elements $G[i, j]$ represent the probability distribution of all pixels that are distance d between a pixel of level i and a pixel of level j. As gray images generally have 256 levels,

the dimension of the GLCM is very large. Many other kinds of texture descriptors can be defined, such as the contrast, dissimilarity, and homogeneity. These are based on the brightness, momentum, and entropy, which are related to properties of the distribution statistics, such as the regularity, or average, variance, and correlation. In this paper, we used four basic texture descriptors in the GLCM matrix G: the contrast, homogeneity, entropy, and momentum.

The contrast, defined by Eq. (1), is the difference in luminance or color. The contrast enables us to distinguish objects. In real scenarios, often, there may be a low contrast between the background and the vehicle. This makes it difficult to improve the accuracy of the detection and classification schemes. The accuracy of existing vehicle classification schemes in low contrast conditions is not sufficient to ensure the success of ITS.

$$\text{Contrast} = \sum_i \sum_j |i-j|^2 G[i, j] \qquad (1)$$

By homogeneity, we mean the spectral homogeneity, which is defined in Eq. (2). We used

homogeneity as a texture feature for a Bayesian classifier. However, we cannot discriminate vehicle types well using only the contrast and homogeneity.

uncertainty of the information source. Mutual data measures the mutual dependence of two random variables and can be used as a measure of similarity.

$$\text{Homogeneity} = \sum_i \sum_j \frac{G[i,j]}{1 + |i-j|^2} \qquad (2)$$

$$\text{Entropy} = \sum_i \sum_j G[i,j](-\log G[i,j]) \qquad (3)$$

Entropy is a measure of information content, which is defined in Eq. (3) as the average

Energy can usually be used to distinguish between vehicle types. Energy is defined by the following equation:

a Images obtained from a visual camera during the daytime

b Images obtained from a visual camera at night

Fig. 6 Images obtained from a visual camera during the daytime and at night. **a** Images obtained from a visual camera during the daytime. **b** Images obtained from a visual camera at night

$$Energy = \sum_{i-j} G[i,j]^2 \qquad (4)$$

3.4 Feature extraction of thermal images

We collected real-time videos from visual and thermal cameras, operating both at day and night. The collected video dataset comprises two sequences, one for the visual images and one for the thermal images. The thermal images were obtained from FLIR ONE [33], which consists of a thermal camera with a resolution of 160×120 pixels and a recording speed of 10 frames-per-second (fps), and a visual camera with a resolution of 1280×720 pixels and a recording speed of 29 fps.

Figure 6 shows visual images obtained from FLIR ONE during the daytime and during the night. Vehicles can be classified by visual images obtained from a RGB camera during the daytime, but vehicles cannot be classified by visual images obtained at night unless there is sufficient illumination. Therefore, another type of data is needed as input to a vehicle detector and classifier at night. Thermal imaging data could be suitable for this application.

Figure 7 shows thermal images from the FLIR ONE taken during the day and at night. The thermal images obtained during the day contain fewer features that can be used for classification purposes than visual images obtained during the day. However, thermal images obtained at night contain more features that can be used for classification purposes than visual images obtained during the night, as shown in Figs. 6b and 7b.

The vehicle can be identified by the headlight and the shape including the ratio of the width of the vehicle to the height of the vehicle then applied image segmentation and pattern analysis techniques. However, the headlight makes it difficult to classify vehicle types using visual video images taken at night, whereas thermal video cameras have an obvious advantage in the case of nighttime surveillance.

The headlights can be detected by identifying bright masses of pixels in the ROI. These can be identified using morphological operations [34] or via template matching [35]. However, in practice, these methods are not efficient when applied to all kinds of traffic scenes and camera exposures. During the day, vehicle types can be classified by the shape of the headlight or the distance between the headlights. However, most vehicles have circular headlamps, which emit a circular beam of light at night. This makes it very difficult to distinguish between vehicle types using data captured from visual cameras at

a Images obtained from a thermal camera during the daytime

b Images obtained from a thermal camera at night
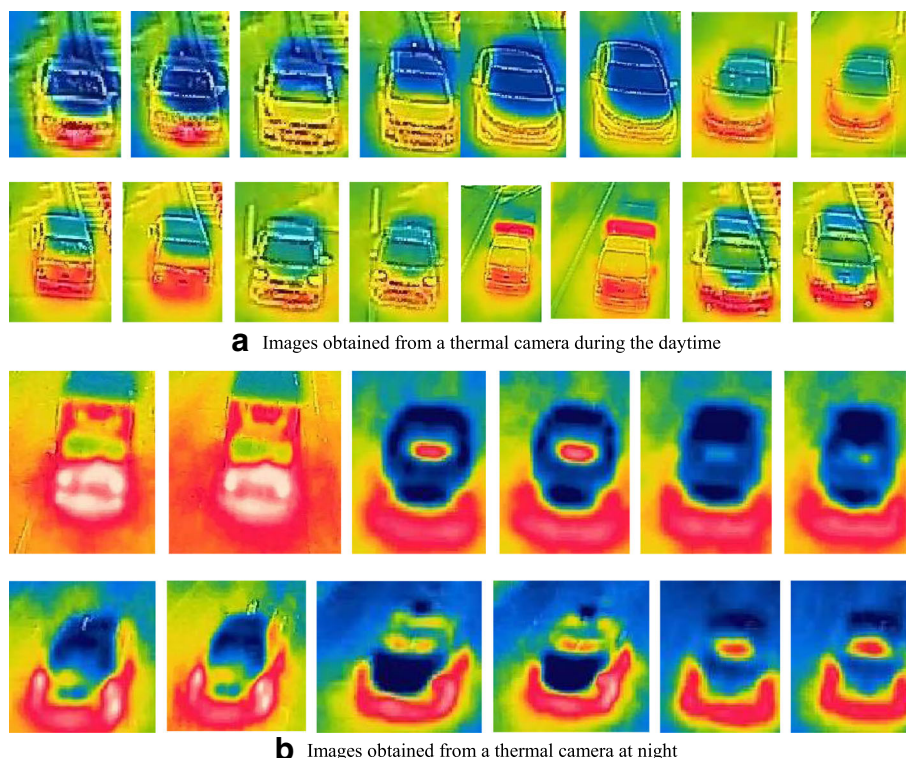
Fig. 7 Images obtained from a thermal camera in the daytime and at night. **a** Images obtained from a thermal camera during the daytime. **b** Images obtained from a thermal camera at night

Table 1 Confusion matrix for the visual image classifier

		Classified					
		d1	d2	d3	d4	d5	d6
Actual	d1	151	10				
	d2		101			11	10
	d3			109	1		
	d4				90	1	
	d5				2	89	
	d6		11		10		171

Table 3 Confusion matrix for the thermal image classifier

		Classified					
		n1	n2	n3	n4	n5	n6
Actual	d1	81	9			8	7
	d2	10	42	21	8		
	d3		1	80			
	d4		20		61		
	d5	21				21	9
	d6	32			7		9

night. The vehicle consists of various elements such as the bumper, engine, windshield, and tiers, which have their own heat identification depending on the type of vehicles. With varying shapes, sizes, and position of each element of vehicles, the vehicles can be classified into vehicle types such as sedan, SUV(sport utility vehicles or recreational vehicles), truck, and bus as shown in Fig. 7b. In this paper, we measured the contrast, homogeneity, entropy, and momentum using thermal images for vehicle classification.

4 Results and discussion

We evaluated our classifiers using a dataset acquired on a local, two-way road. The dataset comprised 767 visual vehicle images and 447 thermal vehicle images. We classified the visual images into six types based on the texture and the ratio of the width of the grill to the height of the grill. We used 6671 visual images and 4005 thermal images as a training set and 767 visual vehicle images and 447 thermal vehicle images as a test-set. To classify the thermal images, we identified vehicle objects then extracted the shapes of the fronts of the cars. We then classified the vehicles in six types based on their texture.

We improved the robustness and accuracy of the model by performing a mixture of Gaussian background subtraction and filtering using functions provided in the OpenCV library. We then extracted a set of features from the GLCM for texture analysis. In Fig. 6a, we define the vehicle types d1, d2, d3, d4, d5, and d6, in a clockwise direction, which are the full-size SUV, the mid-size SUV, the small-size sedan, the full-size sedan, the full-size RV, and the mid-size RV. Table 1 shows the confusion matrix of the visual image classifier, and the accuracy is summarized in Table 2. The overall accuracy of this classifier is 92.7%.

When we divided a vehicle extracted from the visual image dataset collected during the day into the headlight and grill regions, there are sometimes bright blobs caused by white bands on the ground. For example, there are large bright blobs caused by one or more headlights reflecting off the bonnet of a white or light vehicle. There may also be bright blobs caused by the reflections of headlights on the pavement or by sunlight. In addition, there are lots of small bright blobs caused by highlights on the vehicles. There may even be more complicated bright blobs with many components.

In Fig. 7a, we defined vehicle types by d1, d2, d3, d4, d5, and d6, in a clockwise direction. Using the GLCM, we classified the vehicles in terms of the ratio of the width of the front to the height of the front. Table 3 shows the confusion matrix of the thermal image classifier, and the accuracy is summarized in Table 4. The overall accuracy of this classifier is 65.8%.

Table 2 Accuracy of vehicle classification by the visual image classifier

Type	The number of vehicle image	Correct	Accuracy(%)
d1	161	151	93.8
d2	122	101	83.8
d3	110	109	99.1
d4	91	90	99
d5	91	89	97.8
d6	192	171	89.1
Overall	767	711	92.7

Table 4 Accuracy of vehicle classification by the thermal image classifier

Type	The number of vehicle image	Correct	Accuracy(%)
d1	105	81	77.1
d2	81	42	51.8
d3	81	80	98.8
d4	81	61	75.3
d5	51	21	41.1
d6	48	9	17.8
Overall	447	294	65.8

Table 5 Confusion matrix for the visual image classifier (3 types) (t1: sedan, t2: SUV, t3:truck)

		Classified		
		t1	t2	t3
Actual	t1	155	4	2
	t2	3	114	3
	t3		2	108

Table 7 Confusion matrix for the thermal image classifier (3 types) (t1: sedan, t2: SUV, t3:truck)

		Classified		
		t1	t2	t3
Actual	t1	186	12	16
	t2	26	8	2
	t3	26	4	12

When monitoring traffic using low- and medium-mounted video cameras, nighttime conditions present many issues. These conditions are challenging, firstly because the typical daytime surveillance framework, using a RGB camera, cannot work at night, due to the contrast and light sensitivity of the camera, which are generally the moving reflections emerging from the headlights.

Even though thermal images obtained from FLIR ONE at night provide more reliable features for vehicle classification, we cannot distinguish vehicles using thermal images obtained at night because the resolution is insufficient and less identical features. Therefore, it is necessary to identify appropriate types of sensor data and find new methods to detect and classify vehicles at night.

For additional experiments, we defined vehicle types by sedan, SUV, and truck. Table 5 shows the confusion matrix of the visual image classifier, and the accuracy is summarized in Table 6. The correct rates for classes, sedan, SUV, and truck, were 96.3, 95.4, and 98.2%, respectively. The overall accuracy of this classifier is 96.4%. The results show that the proposed method could identify the valid vehicle ROIs in different types effectively. From the table, we found that the regions of sedan and SUV were misclassified due to the similar shapes.

Table 7 shows the confusion matrix of the thermal image classifier, and the accuracy is summarized in Table 8. The correct rates for classes, sedan, SUV, and truck, were 86.9, 22.2, and 28.6%, respectively. The overall accuracy of this classifier is 70.5%. From the table, we found that the regions of SUV and truck were misclassified due to the similar shapes. In particular, the regions of SUV were similar to those of sedan because the

thermal image shapes of the SUV were similar to those of sedan.

5 Conclusions

In this paper, we have presented a smart surveillance system to detect and classify vehicles. We collected videos during the day and at night using FLIR ONE. We selected the front, grill, and headlight of each vehicle as ROIs. For feature extraction, we measured the texture, contrast, homogeneity, entropy, and energy from front view images. This enabled us to classify six types of vehicle. We increased the accuracy of the classification by estimating the ratio of the width to the height of the headlight and the grill. In the experiments, when vehicles were classified into six types, the accuracy of the classifiers based on visible light and thermal images were 92.7 and 65.8%, respectively. When vehicles were classified into three types, the accuracy of the classifiers based on visible light and thermal images were 95.9 and 70.5%, respectively. Even though thermal images at night provide more reliable features for vehicle classification, the accuracy of the classifier using thermal images is lower than that of using visual images in the daytime because the resolution is insufficient and less identical features. To classify vehicles more accurately at night, more reliable features and a thermal camera with a higher resolution are necessary. In the future, we will improve our method for detecting vehicles at night. In addition, we will improve our method by considering various types of vehicles by mixture and validate our method using a wider range of experimental data. In addition, we will conduct additional experiments to show that the proposed method is robust to the weather conditions.

Table 6 Accuracy of vehicle classification by the visual image classifier (3 types)

Type	The number of vehicle image	Correct	Accuracy(%)
t1	161	155	96.3
t2	120	114	95.0
t3	110	108	98.2
Overall	391	377	96.4

Table 8 Accuracy of vehicle classification by the thermal image classifier (3 types)

Type	The number of vehicle image	Correct	Accuracy (%)
t1	214	186	86.9
t2	36	8	22.2
t3	42	12	28.6
Overall	292	206	70.5

Availability of data and materials
We can provide the data.

Authors' contributions
Y-CN and YN conceived and designed the study. YN performed the experiments. YN wrote the paper. Y-CN and YN reviewed and edited the manuscript. Both authors read and approved the final manuscript.

Competing interests
The authors declare that they have no competing interests.

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