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Vehicle Logo Recognition Using Image Matching and Textural Features

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ABSTRACT

In recent years, automatic recognition of vehicle logos has become one of the important issues in modern cities. This is due to the unlimited increase of cars and transportation systems that make it impossible to be fully managed and monitored by human. In this research, an automatic real-time logo recognition system for moving cars is introduced based on histogram manipulation. In the proposed system, after locating the area that contains the logo, image matching technique and textural features are utilized separately for vehicle logo recognition. Experimental results show that these two methods are able to recognize four types of logo (Peugeot, Renault, Samand and Mazda) with an acceptable performance, 96% and 90% on average for image matching and textural features extraction methods, respectively.

KEYWORDS: Vehicle logo recognition, textural features, image matching, vehicle positioning.

1. INTRODUCTION

The vehicle logo is one of the fundamental signs of the vehicles. Automatic vehicle logo recognition plays an important role in intelligent transportation systems in modern cities. Some vehicle logo recognition applications include vehicle tracking, policing and security [1, 2]. Due to the wide variety in the appearance of vehicles of the same vehicle manufacturer, it is difficult to categorize vehicles using simple methods such as morphological functions and so on. In recent years, several studies have been carried out for vehicle-type classification and vehicle manufacturer recognition [3-5].

In [6], the authors used Scale Invariant Feature Transform (SIFT) for vehicle logo recognition. These features are invariant to scale, rotation and partially invariant to illumination differences [7]. In their study, images taken from the rear view of vehicles were used and they obtained 89.5% recognition accuracy. However, it was reported that this system did not have real-time performance and the speed of recognition process were not mentioned in this article. In another work [8], a new approach for vehicle logo recognition from frontal view was presented with 93% recognition accuracy. In this research, the vehicle manufacture and model were treated as a single class and recognized simultaneously and no results for recognition speed were reported. In [9], a car detection system is presented based on color segmentation and labeling, which performs color recognition. Author of [3] used textural features such as contrast, homogeneity, entropy and momentum for frontal view of vehicle images. The classification accuracy of their work was reported 94% using a three-layered neural network. In [3], the processing times are also not reported.

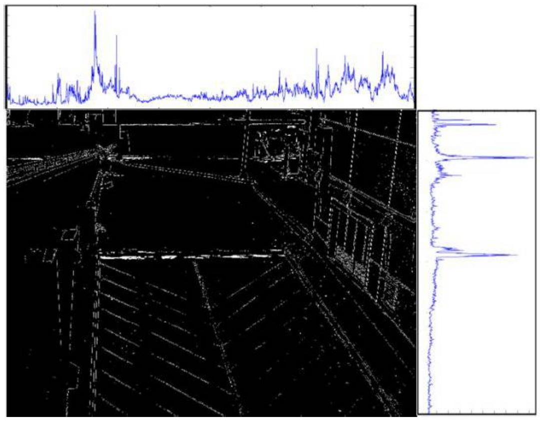
In this research, an autonomous system that aims at obtaining reliable real-time vehicle model recognition for moving vehicles is presented; first by locating the license plate in a vehicle frontal view image and detecting the region of interest over the vehicle, including logo area. Then, the vehicle logo is identified with two different methods: image matching and textural features extraction. This system is flexible and can be used in any situation with an acceptable real-time recognition rate compared to the existing methodologies.

The rest of this paper is organized as follows. In the next section, the proposed system is introduced. In Section 3, the image matching technique and textural features extraction, which are used in the proposed method, are described. Section 4 provides experimental results and Section 5 concludes our study.

2. PROPOSED METHOD

The proposed system for vehicle logo recognition is composed of two phases. The first phase is to build a prototype of the main image. The main image is the image that is taken from an empty scene of interest, i.e. a scene that includes no vehicle or any other moving objects (Figure 1.a). The prototype of an image is defined as the vertical and horizontal projections (histograms) of its edges. In the proposed system, the red band is used to convert a given image into grayscale image and Sobel edge detection is used to detect edges. In this phase, we also count the number of pixels, T_m, laying on the edges for the further processing in the next phase. Figure 1.b shows an example of vertical and horizontal histograms of the main image that is taken from an empty parking entrance.

(a)



(b)

Fig. 1. (a) A parking entrance with no vehicle (main image) (b) Detected edges with vertical and horizontal projections of the pixels lying on the edges.

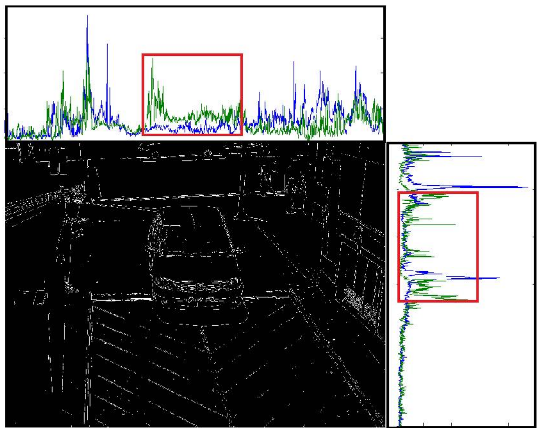
The second phase is the recognition phase where the logo of a vehicle in the given image is identified. This phase consists of three steps. The first step is to investigate whether there is a vehicle in the image or not (vehicle detection step). To this end, the proposed system converts the test image into a gray-scale image and detects the edges on the converted image. Then, the total number of the pixels laying on the edges of the test image, T_t, is calculated. If $500 \leq |T_m - T_t| \leq 5000$, we conclude that there is a vehicle in the scene. Furthermore, if , we may conclude that there are more than one moving cars in the scene. These boundaries were obtained according to our empirical experiments.

In the second step of this phase, the prototype of the test image is built and compared with the prototype of the main image. An example of this comparison is shown in Figure 2. As this figure shows, there are two ranges on vertical and horizontal projections that the histograms of test image have different values, say over 20%, with the histograms of the main image. Therefore, we define a rectangle with the widths and the heights equal to the widths and the heights of the measured ranges in the vertical and horizontal projections respectively.

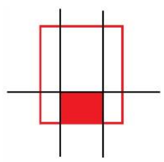
As it is seen in Figure 2.c, one sixth of the obtained rectangle is selected to reduce the number of calculations. This area of interest more likely contains the license plate and the logo. The size of the area of interest depends on the width and the length of the obtained rectangle; the bigger the moving object, the bigger the size of the rectangle. We should note that in case that there are two or more vehicles in the image, the size of the obtained rectangle will be larger accordingly.

The third step, the last step in this phase, is to recognize the logo in the area of interest. In this step we use image matching and textural features extraction methods. These methods are described in the next section for immediate reference. The block diagram of the proposed system is demonstrated in Figure 3.

(a)



(b)



(c)

Fig. 2. (a) A parking entrance with one vehicle (b) Prototype comparison of the main image and the test image (c) the extracted rectangle that contains license plate and logo.

3. RECOGNITION TECHNIQUES

3.1 Image Matching

The Normalized Cross-Correlation (NCC) is one of the most popular methods for image matching. This method is one of the basic statistical approaches for image registration. It is used for template matching or pattern recognition. Template can be considered a sub-image from the reference image, and the image can be considered as a sensed image. In [10], the authors have proposed a method of medical image registration by template matching based on NCC.

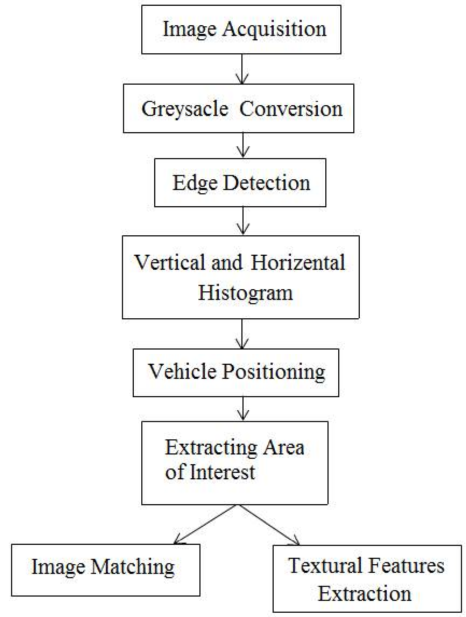


Fig. 3. Block diagram of the proposed system.

In [11], a fast pattern matching algorithm is proposed based on the NCC criterion by combining adaptive multi-level partition with the winner update scheme to achieve an efficient search. In [12], the author has proposed a combined approach to enhance the performance of template matching system using image pyramid in conjunction with Sum of Absolute Difference (SAD) similarity measure. Based on experimental results, it was found that the capabilities provided by the proposed method in [12] significantly improved the accuracy and execution time of template matching system. From the review of literature, it is observed that the template matching algorithm based on NCC is one of the best approaches for matching the template with same image accurately. In this paper, we use NCC as a model to recognize vehicle logos. The 2D NCC is calculated using Eq. 1.

$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - \overline{f}_{u,v}][t(}{\{\sum_{x,y}[f(x,y) - \overline{f}_{u,v}]^2 \sum_{x,y}[} \quad (1)$$

In this equation, f and t are the input vehicle image and the logo (template) images, respectively, $\bar{t}$ are the mean gray-level value of the template, $\overline{f}_{u,v}$ is the mean of $f(x,y)$ in the region under the template, (x,y) stands for position on the main image and (u,v) stands for position on the template.

In the proposed method, the template images are scaled up and down in order the proposed system become scale invariant. The template images are scale down until the width of the template image is 4 times smaller than the width of the sub-image cropped from the test image (area of interest), and scale up until the width of the template is equal to the width of the area of interest.

3.2 Textural Features Extraction

For each retrieved original image, Gray Level Co-occurrence Matrix (GLCM) [13] is used to capture the spatial dependence of gray-level values for different angles of pixel relativity (0°, 45°, 90°, and 135°). Each matrix is run through probability-density functions to calculate different textural parameters. After analyzing the color features of the focused image, the textural features are extracted. In one review, 21 textural parameters were identified [14]. However, another report indicated that only three textural parameters were useful in identifying logo recognition; contrast, homogeneity, entropy and momentum [9]. In this research, three textural parameters are used in identifying image characteristics: entropy, energy, and homogeneity; defined as below [15]:

$$Entropy = -\sum_i \sum_j P_d(i,j) \log P_d(i,j) \quad (2)$$

$$Energy = \sum_{i=1}^{n} \sum_{j=1}^{n} P_{(1,0)}(i,j)^2 \quad (3)$$

$$Homogeneity = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{\{P_{(1,0)}(i,j)\}}{\{1+(i-j)^2\}} \quad (4)$$

where d is the distance between two neighboring resolution cells; q is the angle between two neighboring cells; $P_{(1,0)}(i,j)$ is joint probability density function at d=1 and q=0.

4. EXPERIMENTAL RESULTS

The automatic and real-time vehicle logo recognition of moving cars faces many challenges. Therefore, preparing a proper dataset is essential to enhance the input data and making it more suitable for the next processing steps. 210 images from the vehicles were captured in noon with natural ambient lightening in a public parking of a mall (Hyperstar, Tehran, Iran) (Figure 4). A CCD digital camera (G12 Powershot, Canon) was used to capture images between 12:00 AM and 13:00 AM with 5 seconds interval in June 2013. Obtained Images are 1600×1200 pixels. In the experiments we use four conventional Iranian vehicle logos as shown in Figure 5. To extract the textural features, we measured textual parameters for 24 rectangles (six images for each type of logo i.e. Peugeot, Renault, Samand and Mazda). Table 1 shows the value of textural parameters (in pixel) for each type of the vehicle manufacturer.

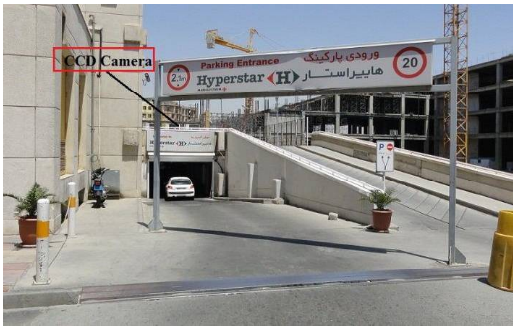
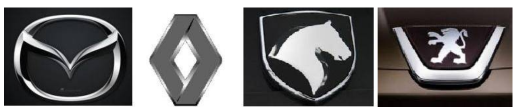


Fig. 4. The place that datasets were prepared there.



(a) (b) (c) (d)

Fig. 5. Logos of vehicle manufacturers (a) Mazda (b) Renault (c) Samand (d) Peugeot.

Table 1. Textural parameters for four type of vehicle logo.

Manufacturer	Entropy (±10%)	Energy (±20%)	Homogeneity (±15%)
Peugeot	7455	2456	7675
Renault	4546	4657	5656
Samand	5565	5568	8854
Mazda	3125	5446	3435

Table 2 shows the performance of the proposed system with two methods for the recognition of the logos. As it is seen, image matching technique has more precision compared to the textural features. However, it is more time consuming. One of the important advantages of these methods is that their results are not dependent to the color of the logos.

Table 2. Performance of two proposed methods for vehicle logo recognition.

Manufacturer	Image Matching		Textural Features Extraction	
	Precision (%)	Speed (s)	Precision (%)	Speed (s)
Peugeot	98.1	3.7	91.4	2.1
Renault	97.5	3.7	92.9	2.1
Samand	93.4	3.7	86.7	2.1
Mazda	96.0	3.7	89.1	2.1
Average	96.2	3.7	86	2.1

5. CONCLUSION

In this study, we proposed an automatic system for vehicle logo recognition. We used two methods to recognize the logos of interest; image matching and textural features. Experimental results showed that these two methods are capable to recognize four types of logo with an acceptable performance, 96% and 90% on average for image matching and textural features extraction methods, respectively. However, the textural features was less accurate than the image matching, it was about 80% faster than it. These two methods can be used for FPGA based programmable boards for increasing the speed of processes. The proposed system that presented in this article can be used as a commercial system for traffic monitoring, tracking stolen cars, managing parking toll, red-light violation enforcement, border and customs checkpoints, etc.

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