Automatic Vehicle Recognition System

David Santos

Abstract—In modern society, due to the high crime rates and high traffic accidents the feeling of insecurity and threat is increasing. The need for the establishment of defence and prevention mechanisms has encouraged studies to develop an automatic recognition systems, which should for example, have the ability to recognize vehicles at a certain distance.

The work reported here focuses on the implementation of two different methods, both relying on the analysis of vehicle external features. The first method evidences the external shape of the vehicle, especially its measures and edges, while the second considers features computed from the vehicle lights, notably the orientation, eccentricity, position, angle with vehicle license plate and its shape contour. Both methods are then combined in order to obtain the proposed automatic vehicle recognition system.

Experimental results indicate that vehicle external features can be exploited as a feasible technique for automatic vehicle recognition showing a correct recognition rate of 88% on a database acquired at the IST parking.

Index Terms—Automatic Vehicle Recognition, Image Processing, Vehicle Features Extraction, Vehicle Shape.

I. INTRODUCTION

The automatic vehicle detection and recognition has become, in the last years, an important subject of study. Many related applications that have been developed, such as self-guided vehicles, driver assistance systems, intelligent parking systems, measurement of traffic parameters and probably the two most important, related with surveillance problems for fighting crime and preventing terrorism, and accident prevention, continue to suggest that a vehicle recognition system is a good manner to help some different areas such as safety, Intelligent Transport Systems and Traffic Management.

One of most common approaches to vehicle detection is using vision-based techniques to identify vehicles from images or videos. However, due to the wide range of vehicles colors, sizes, orientations, shapes, and poses, developing a robust and effective vision-based vehicle detection system is very challenging.

On the other hand, due to the uncountable number of different vehicle manufacturers and models in our market, the difficulty of building an efficient and complete vehicle recognition system is understandable, and so the method here proposed is a “work in progress” approach.

This project aims to develop an automatic vehicle detection and recognition system based on vehicle's external features, which should be robust enough to detect color, vehicle manufacturer and model. The main advantage over other vehicle recognition systems comes from the fact that vehicle external features can’t be easily changed like for example its license plate, since they are components of the vehicle.

Such system could be used in many different situations, for example, in a supermarket parking, or something similar, in order to automatically track all the traffic information during a desired period of time or even be part of a system that helps each supermarket client to find his previously parked vehicle.

It could be also a great update to systems already in use like radar controls and vehicle toll controls in motorways.

Most of the vehicle recognition systems in use exploit vehicle license plate as a keypoint to recognition purposes, therefore to prevent crimes where vehicle license plate could be false, the proposed system is an added value, proving if a recognized license plate correctly matches with respective vehicle color, manufacturer and model.

Knowing that Vehicle's external features are particular to each model, the automatic vehicle detection and recognition system here presented is based on two novel vehicle external features extraction methods developed by the author: Vehicle Shape Features and Vehicle Lights Features that are then combined in order to obtain a robust system.

The first method evidences the external shape of the vehicle, especially its measures, edges, and shape contour, while the second considers the vehicle’s lights features by following several ways to classify them: its orientation, eccentricity, position, angle with vehicle license plate, and its shape contour.

The main contribution of this thesis is the development of these two novel methods that combine, in an original way, a set of vehicles features usually referred to in articles related to vehicle recognition. The achieved results prove that these methods can be exploited as feasible techniques for automatic vehicle recognition, and demonstrate the important contribution of this thesis principally knowing that, the vehicle recognition issue is still at its infancy.

II. PREVIOUS WORK

Since the 1970s, the problem of vehicle detection/classification has been studied by several researchers and now, many studies show that it is possible to detect if a given object is a “vehicle” or a “non-vehicle”.

On other hand, not many existing solutions to recognize vehicle manufacturers and models are available in the literature.

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This project is divided into two main parts: “Vehicle detection” and “Vehicle recognition”. As such, this review of previous work follows a similar structure.

A. Vehicle Detection

In recent years, we have seen a number of systems proposed for the detection, segmentation and tracking of vehicles [1, 7, 8, 17], where robust and reliable vehicle detection is the first step. (Video tracking is the process of locating a moving object in time using a camera).

The majority of methods reported in the literature follow two main steps [1], the Hypothesis Generation methods (HG), where the locations of possible vehicles in an image are hypothesized and Hypothesis Verification methods (HV), where tests are performed to verify the presence of vehicles in the location previously hypothesized, resulting in a “vehicle” or “non-vehicle” automatic classification system.

Hypothesis Generation Methods

Various Hypothesis Generation (HG) methods have been proposed in the literature, which can be classified into one of the following three categories: Knowledge-based methods, Motion-based methods and Stereo-based methods.

1) Knowledge-based methods employ a priori knowledge of certain features of vehicles to hypothesize their location in an image.

A list of some of the most important vehicles’ features often used is: Texture and Color [1], [2], [3], [7], Vehicle Shadow [1], [7], [8], [9], [10], Geometrical Features [7], [8], [10], [11], [12], [16], [17], Vehicle Lights and License Plate.

2) Motion-based methods are statistical methods that do not require sophisticated prior models. The detection of vehicles can be done by analyzing the statistics of the spatiotemporal patterns generated by the vehicle motion in the images [18].

Most of the Knowledge-based methods use spatial features to distinguish between vehicles and background. Motion-based methods may use, as a cue, the relative motion obtained via calculation of the optical flow created by the motion of the vehicles [4], [5], or even the well-known “Median method”, where the median value for each pixel is estimated for a time interval, allowing to distinguish moving from static objects in a sequence of images, and thus to easily segment them from the background.

3) Another type of Hypothesis Generation methods, are stereo-based methods, which make use of stereo information for vehicle detection. Although not so commonly found in the literature, it is possible to highlight two different methods: Disparity Map [6] and Inverse Perspective Mapping [1].

Hypothesis Verification methods

HV methods include tests to verify the presence of vehicles in the locations previously identified and can be divided into two main categories: one use predefined patterns from vehicles and perform some correlation between the selected image locations and the predefined template(s) (Template-based) [14], [15], while the other learn the characteristics of the vehicles from a set of training images that capture the allowed variability in the vehicle class (Appearance-based) [13].

B. Vehicle Recognition

Not many existing solutions to recognize vehicle manufacturers and models are reported in the literature. However, most of the existing methods [19], [20], [21] always use a combination of some of the features already presented in knowledge-based methods overview, to recognize the unknown vehicle.

III. PROPOSED VEHICLE RECOGNITION SYSTEM

The vehicle manufacturer and model recognition method proposed here only uses video sequences of vehicle rear views. This choice was based on the fact that distinguishing features can be extracted from a vehicle’s rear view, such as symmetry, license plate and lights. On the other hand a system based only on vehicle rear views has less computational/implementation costs than another system that would require more than one view (rear, lateral or front) of a vehicle.

Like was written in the Introduction, several are the possible scenarios for a real application of the proposed system. Fig. 1 illustrates some examples.

Fig. 1. - Example of a proposed system real application.

The proposed vehicle detection and recognition system is composed by four main modules:
1) **Vehicle Segmentation**: The first module intends to correctly segment the “unknown” vehicles from the background and then extract, from the video, an image with an aligned rear view of each vehicle. This corresponds to the vehicle detection stage;

2) **Vehicle Feature Extraction**: The proposed Vehicle Features Extraction module has three main components, devoted to the computation of features to be used for recognition purposes. Three types of features are computed: Vehicle Shape, Vehicle Lights and Vehicle Color;

3) **Vehicles Database processing**: Module number three is about the System Database, where the author gives details about its specifications, and all the procedure to correctly add a new vehicle to it. It’s important to refer that to go on with Vehicle Recognition the vehicles database should be previously created.

4) **Vehicle Recognition (Manufacturer and Model)**: Finally, the fourth module, named Vehicle Recognition, computes the similarity between each “unknown” vehicle in a given video and all the rear view images of vehicles stored in the database, determining the one more likely to represent the “unknown” vehicle’s manufacturer and model. Vehicle Color is a feature given as output to characterize the “unknown” vehicle.

An overview of implemented method is presented, in the form of a block diagram, in Fig. 2.

### A. Vehicle Segmentation

For this purpose a motion segmentation technique is employed, which relies on a correct estimation of the sequence background, and subsequent extraction. An overview of this procedure is shown in Fig. 3 (n is the frame number of the video sequence):

**Background Estimation**
In the type of application being considered, the camera capturing the video sequence is typically static. Therefore, the proposed system considers the first frame of a new sequence as a good background estimation. After that, a background refreshment method is implemented, which has the capability of, with an interval of 5 frames, updating the image of the background.

**Background Extraction**
One may suggest that simply performing background subtraction to the images of the video sequence is enough for foreground segmentation. In fact, this technique has been widely used to segment dynamic scenes in the cases where the camera is fixed. Thus, after detecting a new “unknown” object in the video and choosing a frame in which it is aligned with the camera, the proposed method performs an automatic luminosity adjustment between this frame and the updated background image currently available, before proceeding with the subtraction - an example is shown in Fig. 4.

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Fig. 2. Overview of the proposed vehicle recognition system.

Fig. 3. Overview of vehicle segmentation module.

In the following, various steps are illustrated with images from a sample video captured for this Thesis, with a Renault Clio entering the parking garage of IST.

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As mentioned above, the proposed method uses all the features that can be correctly extracted from an aligned rear view of a vehicle to proceed with its recognition.

The Vehicle Feature Extraction module is composed by three main parts: Vehicle Shape Features Extraction, Vehicle Lights Features Extraction and Vehicle Color Feature Extraction.

Vehicle Shape Feature Extraction
Looking at the rear image of a vehicle it is easy to understand that there are several features that can be extracted from its shape, to be used for recognition purposes. The proposed system is implemented to extract three such vehicle’s features, notably: a width/height coefficient, a binary edges map and the vehicle’s outer contour.

The vehicle shape features are extracted using the Vehicle Segmentation results. However this segmentation is further improved with a “horizontal mirroring method”, developed by the author.

Based on some symmetry points in vehicle shape, this method allows the system to fix some remaining errors. Fig. 6 illustrates an example.

Considering that the bottom part of almost all vehicles’ shapes (rear bumper, wheels, etc) is very similar, only the top ¾ of the vehicle segmentation is used for shape features extraction, to highlight each vehicle’s singularities:

1) Width/Height Coefficient: To be robust to variable distances to the static camera, all vehicles’ rear images were initially resized. However, the vehicle’s original shape aspect ratio was maintained and can provide a good filter to distinguish some vehicles. Therefore, before each segmented vehicle is cropped into ¾ of its height, its width/height coefficient is computed.

2) Binary Edges Map: It is easy to understand, while looking into a vehicle from a rear position, that its edges are among the most distinguishing visual characteristics that people use to differentiate vehicles between themselves. Having this consideration well present, a “classic” Sobel Filter is applied to obtain an Edge map of each vehicle shape, which is then improved with a 2x2 dilatation, as the example in Fig. 7 illustrates.
3) **Vehicle’s Outer Contour:** The third feature considered in this proposal represents a novel approach in the field of vehicle recognition. It has been based on the work developed by several authors e.g., for human gait recognition [23, 25].

This proposal consists in tracing the outline of the binary vehicle’s shape, i.e., its outer contour, following its border points in an ordered way, to allow the computation of a signal with the distances between these contour pixels and the shape’s centroid. The Euclidean distances (1) between the coordinates of each outer contour pixel, \( Q = (r, s) \), and the centroid, \( P = (p, q) \), are computed and stored, forming a distance signal, which can be represented as illustrated in Fig. 8.

\[
|PQ| = \sqrt{(p - r)^2 + (q - s)^2}
\]  

Fig. 8. Distance Signals’ samples.

**Vehicle Light Feature Extraction**

One of the most singular features in each different vehicle is its pair of back lights. In fact, when we take a look at a rear view of a vehicle, their lights combined with its shape are the main cues that we unconsciously use to recognize the vehicle manufacturer and model.

Generally, most vehicle lights have red as its main and more relevant color. Therefore, the first step of the detector should be to correctly find all the red color segments appearing in the segmented vehicle’s image.

The method proposed to detect the red back lights of vehicles is based on the algorithm proposed by Carlos Paulo in [34]. Like in vehicle shape, the Otsu’s method [30] is selected to binarize selected regions in image – see Fig. 9.

Fig. 9. Vehicle Lights detection and binarization.

The vehicle back lights can now be characterized by several features computed from their shape. These features are described in the following:

1) **Eccentricity:** Defined as the ratio of the distance between the focus of the ellipse and its major axis length, eccentricity is a good mathematical parameter to characterize 2-D circular objects and its shape properties. Eccentricity value is normalized between 0 and 1, where an object whose eccentricity is 0 is actually a circle, while an object whose eccentricity is 1 is a line segment.

2) **Orientation:** Another distinctive feature between vehicle lights is its orientation, which, in the proposed work, is defined as the angle between the x-axis and the major axis of the ellipse that has the same second-moments as the region.

3) **Position:** Looking at the rear of a vehicle it’s easy to understand that back lights may have different “y-axis” positions depending on manufacturer and model. Thus, assuming a position to have value “0” when the center of the light is at the top of the vehicle, and "400" when it is at the bottom, a new reliable measure for vehicle recognition is proposed.

4) **License Plate Angle:** Knowing that all vehicles have a license plate and its position is variable depending with the vehicle manufacturer and model, another new feature is proposed. License plate angle is the angle between the x-axis that corresponds to the bottom of the license plate and a line that crosses the center of the back light on the left and the bottom of the license plate in the center of the vehicle.

5) **Light’s Outer Contour:** Similarly to what was proposed to describe the vehicle’s outer contour, a distance signal is computed, now to characterize each back light’s outer contour.
Vehicle Color Feature Extraction

In security and surveillance issues it is understandable that indentifying the vehicle color is an important task, and as such it must be considered by the system being proposed. Beyond it is something that is hard to change in a short time, vehicle’s color can also be easily identified at a considerable distance and so constitutes a powerful recognition feature. To perform the vehicle’s color detection, the proposed method uses a well-known color model called HSV [24].

Based on the fact that sometimes it’s not easy to distinguish one color from another, ten color categories were implemented: white or light gray, black or dark gray, gray, red, orange, yellow green, blue, purple and Pink.

C. Vehicle Database Processing

In any recognition system a good Database is essential, so the same happens in a Vehicle Recognition System. The database has a major relevance since it is one of the responsible for a high recognition performance.

As shown in the System Overview Diagram – see Fig. 1, Vehicle Database includes the module “Vehicle Feature Extraction” from the main recognition system, however, with a slight difference, as in this case Vehicle Feature Extraction is not applied to vehicles segmented from an input video, but to rear view vehicle images previously loaded to the system. In order to keep the system up to date, its database should be continuously updated with new manufacturer and model vehicles.

D. Vehicle Recognition

Based on what was written above, it is easy to conclude that Vehicle Manufacturer and Model Recognition is performed through a similarity computation between each “unknown” vehicle in a given video and all the rear view images of vehicles stored in the database.

The computation of similarities is done separately for the features computed from the vehicle shape and from the back lights: Shape Similarity (similarity between all the features extracted from vehicle shapes) and Lights Similarity (similarity between all the features extracted from vehicle back lights).

After computing these two similarity values, they are combined (Vehicle Similarity) for recognizing the database vehicle more likely to correspond to the “unknown” vehicle being tested, thus identifying its manufacturer and model. The vehicle’s color is also automatically determined.

Shape Similarity

To perform Shape Similarity it is necessary to compute the similarity between each extracted shape feature of a given probe (i.e. “unknown” segmented vehicle) and all the vehicles with descriptions stored in the database:

1) Width/Height Coefficient Similarity (WHCS): Since this coefficient is a number, its similarity is obtained by a simple normalized subtraction (2):

\[ WHCS = \frac{|W_{HC_{\text{probe}}} - W_{HC_{\text{database}}}|}{\max(W_{HC_{\text{probe}}}, W_{HC_{\text{database}}})} \]  \hspace{1cm} (2)

2) \( \frac{1}{4} \) of Vehicle Binary Segmentation Similarity (VBS): To compute the similarity between Vehicle Binary Segmentations, a correlation method is implemented (3), where VBS are matrices of the same size \([m \times n]\), each one corresponding to a Vehicle Binary Segmentation.

\[ VBS = \frac{\sum_{m,n}(V_{BS_{\text{probe}}} \cdot V_{BS_{\text{database}}})}{\sum_{m,n} V_{BS_{\text{probe}}} + \sum_{m,n} V_{BS_{\text{database}}}} \]  \hspace{1cm} (3)

3) Binary Edge Map Similarity (BEMS): In order to estimate the Binary Edge Map similarity between probe and database Maps, a Normalized 2-D cross-correlation is implemented [27]. Thus, the higher correlation coefficient is considered as the similarity value between probe and database Maps.

4) Vehicle’s external shape Distance Signal Similarity (VDSS): Euclidean distance between the computed distance signals for the probe and the database vehicles is computed in order to estimate their similarity (4):

\[ VDSS = \sqrt{\sum_{i=1}^{n}(V_{DS_{\text{probe}}}(i) - V_{DS_{\text{database}}}(i))^2} \]  \hspace{1cm} (4)

Where \( VDS \) are vectors of the same size \([n]\), each one corresponding to a Vehicle’s external shape distance signal.

Finally, the Shape Similarity is obtained according to equation (5), in which different “weights” were selected from an exhaustive set of tests to give more importance (larger weights) to the more discriminative features.

\[ \text{Shape Similarity} = 10 \times (1 - WHCS) + 20 \times VBS + 30 \times BEMS + 40 \times (1 - VDSS) \]  \hspace{1cm} (5)

Lights Similarity

Once again, to calculate the Lights Similarity, is necessary to compute the similarity between each extracted light features of a given probe (i.e. “unknown” segmented vehicle) and stored vehicles in the database:

1) Lights Binary Shape Similarity (LBSS): This similarity is computed using the same correlation method explained for the shape similarity, using equation (3).

2) Eccentricity Similarity (ES) / Orientation Similarity (OS) / Lights Position Similarity (LPS) / License Plate Position Similarity (LPPS): Since these features are single numbers their similarity is obtained by a simple normalized subtraction, using equations similar to (2).
3) **Light’s external shape distance signal Similarity (LDSS):** This similarity is computed using the same method explained for the shape similarity, according to equation (4).

Combining all the individual feature contributions, the Lights Similarity can be computed by (6):

\[
\text{Lights Similarity} = 
\begin{align*}
21 \times \text{LBSS} + 15 \times (1 - ES) \\
+ 15 \times (1 - OS) + 15 \times (1 - LPS) \\
+ 16 \times (1 - LPPS) + 16 \times (1 - LDSS)
\end{align*}
\]  

Once again these “weights” were arranged to give more importance to the more discriminative features.

**Vehicle Similarity**

Once **Shape and Lights Similarities** have been computed, the final **Vehicle Similarity** is calculated according to (7):

\[
\text{Vehicle Similarity} = 
\begin{align*}
40 \times \text{Shape Similarity} \\
+ 60 \times \text{Lights Similarity}
\end{align*}
\]  

These “weights” were estimated knowing that **Lights Features** are less dependent of the vehicle’s segmentation quality, and so are expected to be more robust than the **Shape Features**.

This way, the system is able to determinate the database vehicle more likely to be the “unknown” vehicle, and so, to conclude about its manufacturer and model.

### IV. Results

Based on the widely accepted FERET methodology for the evaluation of recognition algorithms [28], the performance of the vehicle recognition system proposed in this Thesis is listed in terms of the probability \( p(k) \) that a test sequence (input video sequence) is among the top \( k \) matches, i.e. the correct recognition rate is the probability at the rank 1 among all the matches in the complete database set. The performance statistics are reported as the cumulative match scores. The rank \( k \) is plotted along the horizontal axis, and the vertical axis is the percentage of correct matches [28].

In order to best understand the achieved results, they are divided in three categories: **Shape Similarity Results** based only on Shape Similarity values, **Lights Similarity Results** based only on Lights Similarity values and finally **System Results**, the final **Vehicle Similarity** calculated according to (7).

#### A. **IST - Vehicle Database**

To evaluate the performance of the implemented system, a database was created. This database is composed of a test set, a video with 18 vehicles entering in IST vehicle parking garage, and a database set of 40 images of segmented rear views of vehicles from different manufacturers of different models, both created during June 2008. Although the recording sessions were made on several days, the illumination conditions were very similar. It’s Important to refer that test and database sets were acquired without any special condition of illumination, reflections or foreign shadows reduction.

#### B. **Shape Similarity Results**

The cumulative similarity results at the top most rank is 44 percent – see Fig. 10.

![Fig. 10. Performance evaluation based on extracted shape features.](image)

Although it is believed that the recognition potential of these features is very high, the quality of the vehicle segmentation has to be very good in order to avoid major errors from the binary segmentation correlation or from inconsistent construction of the distance signals; keep in mind that these signals are relative to the Euclidean distance between the coordinates of the segmented vehicle’s boundary pixels and its centroid.

On the other hand, the potential of **edge map feature** can also be reduced if several shadows and foreign objects appear between the camera and the “unknown” vehicle.

Concluding, it is believed that the results would be much better if the vehicle segmentation was more accurate or the filming area had been specifically prepared to the video shooting, avoiding for example shadows, reflections of the sun in vehicle, foreign objects, vehicle’s occluded parts, etc.

#### C. **Lights Similarity Results**

The vehicle recognition results obtained using only the features computed form the vehicle back lights and geometrical considerations, using the **Vehicle Lights Similarity** metrics presented, are plotted in Fig. 11.

Based on extracted lights features the system achieved a correct recognition rate of 71% (12 out of 17 vehicles); it means that the similarity between the light features from the probe and the correct database vehicle are quite evident except...
for some minor flaws. Confirming that, these features show better results than shape features.

Fig. 11. Performance evaluation based on extracted lights features.

In both cases, Vehicle Color Extraction method shows a correct color recognition rate of 100%, since all Identified Vehicle Colors are correct.

The average elapsed computational time for each “unknown” vehicle recognition is approximately 1 minute and 20 seconds for the first method and 10 seconds for the second (using an Intel® Core (TM) 2 CPU 6400@ 2.13GHz processor with 2Gbyte RAM). This different mainly due to the fact that, the cross-correlation done between the two Binary Edge Maps, in first method, has a high computational cost.

D. Vehicle Recognition Results

According to equation (7) the overall proposed system performance is estimated, considering both shape and back light features. The performance results are plotted in Fig. 12.

Fig. 12. Performance evaluation of proposed system.

The system showed a successful recognition rate of 89% (16 out of 18 vehicles).

By analyzing all results, it is possible to conclude that the Lights Feature Similarity method shows better recognition rates than the Shape Feature Similarity method for most of the performed experiments. This is mainly due to the fact that the first method requires a good quality vehicle segmentation, while the second copes rather well with this situation, since the vehicle’s lights are independently identified. Furthermore, each vehicle has always two symmetrical lights which allow the system to select the best one, avoiding some errors that could arise.

Although the difference between the two methods is clear, it is also possible to notice that their combination improves the performance of the proposed system.

In terms of computational cost, approximately 1.5 minutes is required for each vehicle recognition operation.

V. CONCLUSIONS AND FUTURE WORK

Vehicle external features are particular to each model, allowing to distinguish one from others. Many studies in different areas such as safety (crime prevention, surveillance problems), Intelligent Transport Systems (driver assistance systems, intelligent parking systems) and Traffic Management (Traffic Parameters), continue to suggest that a vehicle recognition system is a good manner to help solving some of these problems.

Although software implementations of vehicle detection systems have often been reported in the literature, the vehicle recognition issue is still at its infancy, with the usual systems relying exclusively on license plate recognition. However, the most recent approaches show that the evolution of computer vision techniques is increasing the ability to build a robust vehicle recognition system based on its external features, allowing to recognize also the manufacturer and model.

The main advantage over other vehicle recognition systems comes from the fact that vehicle external features can’t be easily changed like for example its license plate, since they are components of the vehicle. Even more, the recognition can be done at a distance and with relatively lower video quality images.

This project focused on the implementation of two novel vehicle external features methods developed by the author: Vehicle Shape Features and Vehicle Lights Features that are then combined in order to obtain a robust vehicle recognition system.

The first method evidences external shape of the vehicle, especially its measures, edges and shape contour.

The second method considers the vehicle lights features by performing several ways to classify them, its orientation, eccentricity, position, angle with vehicle license plate and its shape contour.

A large number of experimental results, with a database specifically created for this project, have demonstrated that both methods show encouraging recognition rates, even though the first method has proven to be less reliable than the second, notably if the video acquisition conditions are not controlled. This is mainly due to the first method’s proneness to fail when the quality of vehicle segmentation is not so good, while the second is more robust, even if not totally unaffected by this
type of errors. Therefore, better results would be expected if more accurate vehicle segmentation could be achieved.

Nevertheless, the combined results show that when system makes usage of both methods, its performance is clearly increased, from around 45% and 70% of recognition rates for first and second methods respectively, to around 90% for the combined system.

In terms of computational cost, approximately 1.5 minutes were required for each vehicle recognition operation, using an Intel® Core (TM) 2 CPU 6400 @ 2.13GHz processor with 2Gbyte RAM. The average elapsed computational time for each “unknown” vehicle recognition is approximately 1 minute and 20 seconds for the first method and 10 seconds for the second.

Although the achieved results are very encouraging, more experiments should be made to validate the proposed system.

In order to do it, several difficulties should be overcome, such as:

1) **System Database**: The system database should be more complete, including more examples per vehicle (manufacturer and model) to accurately extract their features. To facilitate one of the vehicles’ database demands, an agreement could be done with vehicles companies. And so instead of using segmented real views of the vehicle, the program should be able to use the drawings offered by vehicle companies. This could be also a manner for the system database stay updated;

2) **Video Scenario**: The filming conditions should be enhanced, for example, by building a structure that could minimize some unwanted errors like reflections, wrong vehicle’s position or overlapping vehicles.

In the future, a robust vehicle recognition system could play an important role in global security by fighting crime, and eventually preventing terrorism. This system could be a part of a wide variety of applications that include visual surveillance, and access control, in special environments like motorways or parking lots.

In what concerns the work here developed, there are some improvements that could be included in future work:

1) **Computation Cost**: As presented in previous chapter, the difference between the computation costs of the two implemented method is enormous; the second method is close to real-time while the first one has a cost of over one minute. Based on the fact that this high computational cost is mainly due to the correlation done between the two **Binary Edge Maps**, a faster correlation method should be implemented.

2) **Improve Video Segmentation**: As has been written several times in this work, one of its main flaws is the video segmentation quality, due to the filming conditions and also to the fact that the implemented method is quite simple. Thus, one future proposal for this work is its combination with a more robust video segmentation method in order to increase some of the achieved results.

Yet, and when a precise vehicle segmentation is performed, it is believed that the proposed system can be used as a reliable standalone control system, ensuring high recognition performance.

Concluding, it was proven that the novel and original methods developed by the author can be exploited as feasible techniques for automatic vehicle recognition and have an imperative contribution to the “work in progress” vehicle recognition approach.

**REFERENCES**


