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Robust feature point detectors for car make recognition

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A R T I C L E I N F O

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A B S T R A C T

An Automatic Vehicle Make and Model Recognition (AVMMR) system can be a useful add-on tool to Automatic Number Plate Recognition (ANPR) to address potential car cloning, including intelligence collection by the police to outline past and recent car movement and travel patterns. Although several AVMMR systems have been proposed, the approaches perform sub-optimally under various environmental conditions, including occlusion and/or poor lighting distortions. This paper studies the effectiveness of deploying robust local feature points that can address these limitations. The proposed methods utilize a modification of two-dimensional feature points such as SIFT, SURF, etc. and their combinations. When SIFT gets combined with the multi-scale Harris/multi-scale Hessian methods, it could outperform existing approaches. Experimental evaluations using 4 different benchmark datasets are conducted to demonstrate the robustness of the proposed techniques and their abilities to detect and identify car makes and models under various environmental conditions. SIFT- DoG, SIFT- multi-scale Hessian, and SIFT- multiscale Harris are shown to yield the best results for our datasets with higher recognition rates than those achieved with other existing methods in the literature. Therefore, it can then be concluded that the combination of certain covariant feature detectors and descriptors can outperform other methods.

1. Introduction

Intelligent transportation systems have contributed mainly to the fields of traffic monitoring, vehicle theft control, etc., which ultimately aim to minimize human intervention. In addition to the license plate information, the identification of the exact make and model of cars is useful and provides many additional cues in certain applications. Therefore, similar to an automatic number plate recognition system, a computer vision system that can automatically detect and identify the make and model of vehicles is advantageous, especially when combined with an ANPR system to accurately identify a vehicle. Additionally, the method can act as an efficient tool against car cloning.

Currently, vehicle recognition systems are solely based on ANPR, and the technology is deployed in many applications ranging from cars parked in both public and restricted areas to the detection of vehicles on police/security "watch lists". However, identity theft of vehicles (the process of replacing vehicle registration plates with those from an identical vehicle) is becoming an easy task for criminals to clone a vehicle, thus enabling them to easily commit crimes ranging from petty theft to organized crime. For example, the scale of cloning in Ireland and the UK is currently deemed to be immeasurable. When combined with ANPR, an AVMMR system can provide an extra level of security to fight car cloning since it is difficult for a criminal to steal and use a car registration number when the make, model, and colour of the cloned car is unknown. Reports by police and security organizations have recently indicated that vehicle cloning is more prominent worldwide and leads to security breaches and increased costs. The vendors have commented that the information collected from ANPR have been used by police to discover where a plate has been in the past, to identify whether a vehicle was at the scene of a crime, to identify the travel patterns of vehicle, and even to discover the vehicles that may be associated with each other [1]. These scenarios can be more efficiently addressed by combining ANPR with automatic vehicle make and model recognition so that the make, model, and colour of the vehicle are used to enhance recognition reliability. Moreover, this intelligence information can be shared with other agencies.

Accurate vehicle make and model recognition can be very useful for police camera control, including traffic offenses, car thefts, cloning, automation and terrorist activities, especially when combined with an ANPR system. Recently, a number of vehicle monitoring and security systems have been developed, and these systems are based on ANPR or utilize ANPR to detect the regions of interest. Since it is relatively easy to forge number plates, ANPR alone may not be the most reliable solution. To increase the level of security, ANPR can be related to the car's

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make and model (and optionally the colour), thus resulting in improved surveillance and tracking performances of vehicles from video streams of deployed cameras on roads and buildings. Another benefit of AVMMR is that the amount of footage to be screened can be significantly reduced when an incident is flagged, thus making it very useful for use in forensic investigations. Many techniques have been proposed for the classification of car makes and models.

Various physical vehicle structures in images can be useful for recognizing cars. It can include certain identities of vehicles, such as the shape of different parts, logos, etc. The symmetric structures of the car can be captured with the aid of features such as the symmetric SURF as in Ref. [2]. Grille patterns and headlight patterns also serve to distinguish between different vehicle makes and models. The desired characteristic should be encapsulated in the region of interest (ROI) fed to the part of feature extraction and further processing. The work of this paper aims to develop an Automatic Vehicle Make and Model Recognition system. It is envisaged that such a system will be combined with ANPR technology to fight car cloning. In this work, the deployment of a combination of modified feature point detectors and their use in an AVMMR are examined. The aim was to determine the best approach to maximize the recognition performances under illumination, occlusions and noise artefacts, especially when images are extracted from video cameras installed on motorways, roads, and public places. To achieve this, various approaches have been adopted by modifying the implementation of the detectors through their combinations using a multi-scale decomposition methodology. To validate the results, four datasets available in the literature were used.

The remainder of the paper is organized as follows. Section 2 reviews the existing works related to ANPR and vehicle make and model recognition. Section 3 presents the proposed system with the detailed description of feature extraction and matching in Section 4. Section 5 provides the experimental aspects and results of our work. The results are further analysed in Section 6 and are followed by conclusions in Section 7.

2. Related works

Several algorithms have been proposed to extract vehicle number plates. An ANPR system mainly consists of the plate region extraction and character recognition tasks. The two step approach for license plate recognition described in Ref. [3] follows two major steps: candidate license plate region extraction using a line density filter and license plate verification using a cascaded license plate classifier trained on colour saliency features. Addressing complex scenes that involve reflective glare on license plates still remains a major issue. Rahim and Iman presented an online ANPR system to address unclear license plates, weather, lighting and traffic variations [4]. Number plate segmentation and detection involve several stages, including thresholding, connected component labelling, RANSAC application and character detection using a Support Vector machine (SVM). Prior to the recognition stage, the obtained plates are classified into three classes of clean, medium and dirty and adaptive thresholding is generally used in the next stage to utilize this information. It is then followed by a scale invariant feature extraction and an SVM based character classifier. The plate localization stage proposed in Ref. [5] is based on the strong Convolutional neural network (CNN) architecture to help identify inherent localization failures. A segmentation free optical character recognition (OCR) in this method uses Hidden Markov Models (HMMs) and a Viterbi decoding to complete the process. Another CNN based license plate recognition system is deployed for Chinese plates in Ref. [6]. A detailed review of the major techniques for ANPR can be found in Ref. [7].

Many research works have been proposed in the field of car model recognition. For example, the authors [8] make use of a template matching strategy for finding the similarity of a query car image to a known model in the database. Pre-processing is applied for noise removal, greyscale conversion, and histogram equalization. Then, object detection is achieved by a subtraction operation of the background image. The presence of an object is indicated by a colour difference between the two fields. The last step consists of feature extraction using a Gabor filterbank, which is able to extract the features. The similarity measure between the Gabor jet of the test and the template image is used to recognize the exact match for the test image. The number of vehicle classes is limited to three in this work.

The authors in Ref. [9] used contour features for car recognition and the technique starts by detecting the regions of interest. Then, a Canny operator extracts the image's edges and generates an image pyramid for the edge contour of the car. The features, such as the round rate, Fourier descriptors, direction ratio, and circumference and area ratio of the car wheel, are then computed. The paper shows the results of only 4 classes with no reference to the dataset used. The performance is not very high, mainly because of the poor quality of contour extraction.

In Ref. [10], a car image is segmented initially by applying a background subtraction technique. Using the resulting binary image, which represents the rear-view shape of the car, a number of features can be extracted. The characterization of the car is then extracted from the shape features, back light features, and the colour. Finally, a similarity measure generated from these features allows for the determination of the car model at hand from a list of models stored and registered in a database.

A discussion of the features suitable for vehicle model detection in aerial videos is provided in Ref. [11]. Scale and rotation invariant descriptors are computed from the region of interest moments of the car image. By detecting small image structures, the model of the vehicles can be determined using a suitable classification method. The advantages of the regional moments over the regional covariance descriptors were also reported in the paper. In Ref. [12], a two-dimensional Linear Discriminant Analysis (2DLDA)-based algorithm is proposed and implemented for real-time vehicle model recognition where robust features are obtained by applying 2DLDA on the gradients of the regions of interest extracted relative to the location of the license plate. However, the algorithm is shown to be sensitive to colour variations and light distortions, thus resulting in a recognition accuracy of 94.7%.

A comparative study of different approaches for car make and model recognition can be found in Ref. [13] and it includes Canny edges, Harris corners, Square mapped gradients, Recursive partitioning and local normalization with the kNN and the Naive Bayes classifier for the matching step. These approaches have also been investigated and evaluated using a new approach based on the strength of Harris corners. To achieve this, the algorithms are applied over the region of interest extracted according to the height and width of the located license plate. Testing and evaluation were carried out using a realistic dataset of 262 frontal car images.

The algorithm discussed in Ref. [14] relies on the global and local descriptors of the car image. The global shape descriptors are calculated for the selected edge points in the edge map. Since the objects from the same class (cars in this case) have similar shapes, a local shape descriptor is also computed using the edge points. In addition, appearance features and their descriptors are extracted from the manually segmented regions. The experiments involved only rear-view car images. A 2DLDA-based approach is used and compared against a Principal Component Analysis (PCA) counterpart in Ref. [15] and the results showed that the former outperformed the latter with a recognition performance of 91% versus 85%, respectively. Testing was conducted using a database of 200 training images of 25 car make groups with 8 samples each under varying illumination and occlusion conditions.

Another technique presented in Ref. [16] utilizes a Speeded-Up Robust Feature (SURF) descriptor-based algorithm. The solution was tested on three databases of toy car images in which an accuracy of more than 90% was obtained. A study was conducted in Ref. [17] to evaluate the performance of different algorithms, including the Scale