Computers and Electrical Engineering 56 (2016) 15–29

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Real-time search-free multiple license plate recognition via likelihood estimation of saliency[☆]

Amin Safaei[*], Hongying L. Tang, Saeid Sanei

Faculty of Engineering and Physical Sciences, University of Surrey, Guildford, UK

ARTICLE INFO

Article history:
Received 30 December 2015
Revised 6 September 2016
Accepted 8 September 2016

Keywords:
Automatic license plate recognition
Bayesian
Intelligent transportation system
Localization
Object tracking
Saliency map detection
Shadow removal

ABSTRACT

In this paper, we propose a novel search-free localization method based on 3-D Bayesian saliency estimation. This method uses a new 3-D object tracking algorithm which includes: object detection, shadow detection and removal, and object recognition based on Bayesian methods. The algorithm is tested over three image datasets with different levels of complexities, and the results are compared with those of benchmark methods in terms of speed and accuracy. Unlike most search-based license-plate extraction methods, our proposed 3-D Bayesian saliency algorithm has lower execution time (less than 60 ms), more accuracy, and it is a search-free algorithm which works in noisy backgrounds.

1. Introduction

Nowadays, intelligent transportation systems (ITS) have a wide impact on people's daily activities. Advanced computer vision technologies and automatic license plate recognition (ALPR) systems are used at the core of ITS infrastructure to identify the vehicles licenses. These technologies are required in many applications such as red-light enforcement, speed enforcement, electronic payment systems and traffic surveillance. ALPR process usually consists of four main steps: image acquisition, localization, segmentation, and optical character recognition.

ALPR systems have to cope with challenges such as images taken under different environmental conditions and lightings, sizes, and orientations. The plate numbers may be occluded or have their locations varied. In real-time operations e.g. ITS, ALPR process has to operate fast and accurately. In specific applications, even a single late detection or mis-detection of a moving car through the camera scene may not be tolerable. As such, the problem of improving the performance and accuracy of ALPR systems has become a crucial research area in ITS applications.

Localization is the most challenging step of any ALPR process and is strongly influenced by the accuracy and execution time of the overall system. Several methods have been suggested in the literature for license plate (LP) localization. According to Du et al. [1], since an LP can be distinguished by its contextual features, there is no need to process the entire scene to find the plate number. On the other hand, Anagnostopoulos et al. [2] argued that global image information techniques such as connected component analysis (CCA) can be used. CCA works for both grey level and binary images. This technique scans the image and finds those pixels in a connected component that share similar intensity values.

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Area Editor Dr. E. Cable-Yepez.
* Corresponding author.
E-mail address: a.safaei@surrey.ac.uk (A. Safaei).

http://dx.doi.org/10.1016/j.compeleceng.2016.09.010
0045-7906/

Matas et al. [3] suggested a region-based approach to extract character-like regions. The plate is assumed to be a linear combination of these small regions. Although this method is time-consuming, it is robust to rotation and has a high accuracy.

Broumandnia et al. [4] suggested another localization method called partial image analysis where the image is scanned row by row and the number of edges within each N rows is counted. This method is very fast and simple to implement, however it depends on the plate size and its distance from the camera.

Zunino et al. [5] proposed a method based on hierarchical representation using vector quantization (VQ). Using VQ different (but lower) image resolutions can be achieved where a vector of close pixels can be represented using only one value (such as their cluster centre). Therefore, the regions of interest such as those of LP can be better recognized.

Statistical measurement methods have also been used in LP localization. Lee et al. [6] proposed a method to estimate the LP region by identifying the blocks with high edge magnitudes or high edge variances. Although Lee et al. claim an accuracy of 92.5%, other works such as that proposed by Anagnostopoulos et al. [2], argue that not all the blocks detected by this algorithm are the actual LPs. Probabilistic object tracking in videos introduced by Yalcin et al. [7] is a method for LP location estimation and car tracking in successive video frames. In this method, probability density propagation is used to estimate the object and filter the measurements. According to Ying et al. [8], the algorithm developed by Yalcin et al. can only improve the computation time and not the accuracy.

Most algorithms used in LP localization, such as by Du et al. [1], are based on the presumption that an LP can be viewed as irregularities in the image texture. Rapid changes in the local characteristics of the car image point to the LP location. Although this algorithm is simple to implement and has a high localization rate, the search process is time-consuming and several parameters need to be adjusted.

Search-based approaches often employ a sliding window to scan and search the entire image, which results in high recognition rate. However, they are computationally slow. On the other hand, the methods based on CCA are rapid but require an accurate binarisation step and an accurate and effective threshold selection.

In our earlier work [9,10], we presented a robust search-free LP localization, incorporating hierarchical saliency and a novel search-free method for accurately locating the LP based on the estimation of saliency, local variance and the use of Gabor functions to ascertain the choice of the candidate LP. In comparison with the other methods such as those proposed by Lee et al. [6], Anagnostopoulos et al. [2], Yalcin et al. [7] and Isard et al. [8], this method performs faster and more reliably as it avoids any exhaustive search. For the original saliency map detection (SMD) method introduced by Itti et al. [11], however, further modifications are required to enhance the speed.

One main drawback of most existing algorithms is that they attempt to perform the localization of the vehicles using still images without taking into account the vehicle movement. As a result, they mistakenly detect undesired objects such as trees, road signs, or shadows as salient regions. Therefore exploiting the motion in videos by tracking algorithms can lead to a more efficient ALPR system.

In the last few decades, many researchers have presented the object detection and tracking algorithms. The algorithm presented by Shantaiya et al. [12] uses Kalman filter and optical flow. This method has a high performance in scenarios where detecting moving object in similar background. However is not able to track low resolution object. Kodama et al. [13] uses particle filter and optical flow for object tracking. Similar to [12], this method requires large computation time and is not efficient for tracking objects in low resolution. On the other hand Li et al. [14] uses background cues for tracking objects. Although this algorithm has a high accuracy, it is sensitive to occlusion and illumination changes. A novel tracking algorithm presented by Aslani et al. [15] uses blob analysis for object segmentation and optical flow field vectors for object tracking in traffic surveillance. This method is a more efficient comparing to [12–14]. Though experiments shows that this algorithm is sensitive to camera motion and only works for tracking single objects.

In Bhaskar et al. [16], a unique algorithm for vehicle data recognition and tracking using Gaussian mixture model and blob detection methods is proposed.

Wang et al. [17] proposed an effective real-time background extraction and moving object detection method with less memory usage comparing to the methods such as Chiu et al. [18]. Jiang et al. [19] proposed another background extraction algorithm, i.e. Partition Weighed Histogram (PWH). The algorithm assumes that the background does not vary considerably in a small neighborhood over time.

Russell et al. [20] also proposed a simple method for detecting and removing shadows in traffic videos by using spatial intensity relationship between pixels associated to a scanned image line. This method performs the classification on image lines to differentiate between the background and the shadow and has a high accuracy rate.

In designing a robust tracking algorithm, the moving shadows cause major problems. Yuan et al. [21] proposed a shadow detection technique with a surface descriptor, named colour shade. This algorithm has high accuracy and can remove shadows from the images and reconstruct the image without shadows. However, the algorithm is time-consuming, since it uses the gradients of the images and the derivations in two directions. Tian et al. [22] discussed and evaluated a number of shadow detection algorithms. One important and conventional method for scene shadow detection uses texture analysis. In this method, in order to distinguish between shadows and moving objects, texture features are analysed to distinguish the moving regions and the background frames. Both structural and statistical approaches have been used for image texture analysis.

Haralick et al. [23] proposed fourteen statistical features to describe a texture. Authors in [23] believe that texture is an important characteristic for identifying the objects or ROIs in an image and they describe a method to estimate texture features based on grey tone spatial dependencies. A grey level co-occurrence matrix, also referred to as a co-occurrence