



Ensemble of adaboost cascades of 3L-LBPs classifiers for license plates detection with low quality images



Meeras Salman Al-Shemarry^{a,*}, Yan Li^a, Shahab Abdulla^b

^a School of Agricultural, Computational and Environmental Sciences, Faculty of Health, Engineering and Sciences, University of Southern Queensland, Australia

^b Open Access College, University of Southern Queensland, Australia, QLD 4350, Australia

ARTICLE INFO

Article history:

Received 4 May 2017

Revised 22 August 2017

Accepted 11 September 2017

Available online 21 September 2017

Keywords:

License plate detection (LPD)

Region of interest (ROI)

Adaboost Learning algorithm

Cascade classifier

Local binary pattern classifiers (LBP)

ABSTRACT

Due to the plate formats and multiform outdoor illumination conditions during the image acquisition phase, it is challenging to find effective license plate detection (LPD) method. This paper aims to develop a new detection method for identifying vehicle license plates under low quality images using image processing techniques. In this research, a robust method using a large number of AdaBoost cascades with three levels pre-processing local binary patterns classifiers (3L-LBPs) are used to detect license plates (LPs) regions. The method achieves a very high accuracy for detecting LP number from one vehicle image. The proposed method was tested and trained with the images from 630 and 400 vehicles, respectively. The images involve many difficult conditions, such as low/high contrast, dusk, dirt, foggy, and distortion problems. The experimental results demonstrate very satisfactory performance for LP detection in term of speed and accuracy, and were better than the most of the existing methods. The processing time for the whole testing LPD system was about 1.63 seconds to 2 seconds. The overall probability detection, precision, and f-measurement are 98.56%, 95.9% and 97.19%, respectively; with false positive rate 5.6%.

© 2017 Elsevier Ltd. All rights reserved.

1. Introduction

Nowadays, intelligent transportation systems (ITSs) play a very important role in our daily life in many aspects. An ITS normally consist of two parts: a smart infrastructure system and an automatic number plate recognition system (ANPR) (Anagnostopoulos, 2014; Anagnostopoulos, Anagnostopoulos, Loumos, & Kayafas, 2006). It is necessary to examine and observe the road traffic to avoid unacceptable behaviors using surveillance applications (Castello, Coelho, Del Ninno, Ottaviani, & Zanini, 1999; Chakraborty & Parekh, 2015; Duan, Duc, & Du, 2004; Sarfraz et al., 2013). The first successful ANPR was recorded in 1978 for the detection of stolen cars in UK. Such an ANPR system is also named as optical character recognition (OCR), automatic license plate recognition (ALPR), or car plate recognition (CPR). An ANPR system has many different applications for a variety of purposes, such as for highway road tolling systems, security systems, parking management systems, and so on (Azad & Ahmadzadeh, 2014; Baharlou, Hemayat, Saberkari, & Yaghoobi, 2015; Dehshibi & Allahverdi, 2012). Currently, the ANPR still has big problems which are described below. Therefore, many researchers in the field of machine vision have

tried to find modern and reliable methods to build an ITS. The main objective of an ANPR system is to identify a vehicle license plate from images or a sequence of images in a video. Those images are often captured from high quality cameras installed on the street lights, road traffic signs, high buildings or motorway overpass (Azam & Islam, 2016; Valera & Velastin, 2005; D. Zheng, Zhao, & Wang, 2005). LPD means extracting LP number from captured image which is the one of the most important stage of ALPR system (D. Zheng, Zhao, & Wang, 2005). The ANPR system involves four stages as shown in Fig. 1. The first one is the vehicle image acquisition using a camera. The accuracy of an ANPR system depends on the parameters of a camera, such as type, resolution, light, shutter speed, and the installation method. The capture vehicle image needs pre-processing stage to reduce the noise on LP background information and enhance the processing speed for detection and recognition stages. The key requirements for a high quality ANPR are high accuracy and processing speed for real-time application (Angelova, Krizhevsky, Vanhoucke, Ogale, & Ferguson, 2015). The second stage is to detect the LP area from acquired images. The LP detection stage depends on the quality of the images and the type of processing methods used to obtain the LPs images (Hongliang & Changping, 2004; Yousef, Al-Tabanjah, Hudaib, & Ikrai, 2015). In this stage, the LP region extracts from vehicle image as a region of interested and eliminates the unwanted background features by using many pre-processing algorithms and learning algorithms for

* Corresponding author.

E-mail addresses: MeerasSalmanJuwad.Al-Shemarry@usq.edu.au (M.S. Al-Shemarry), Yan.Li@usq.edu.au (Y. Li), Shahab.Abdulla@usq.edu.au (S. Abdulla).

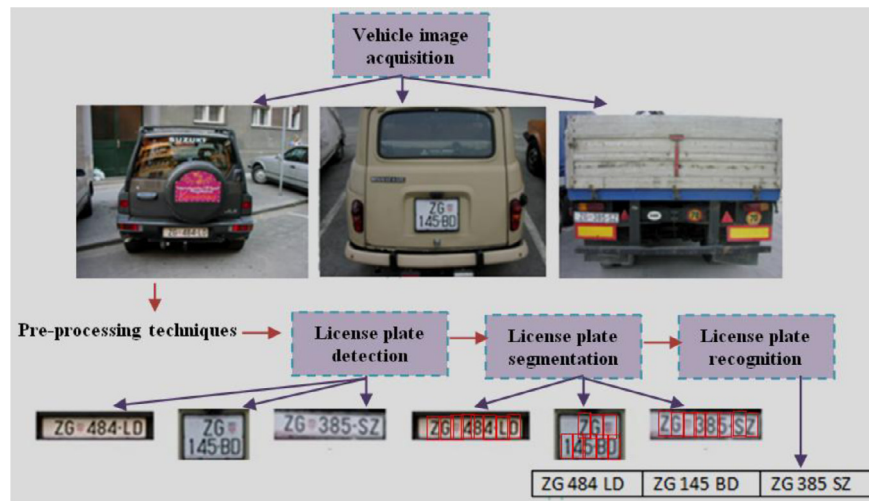


Fig. 1. ANPR system stages.

different features of LP, such as edge information, texture features and color features. The aims of using learning algorithm for this stage to obtain high performance in terms of the detection rate and processing time for testing phase. Moreover, the trained model from those algorithms can detect multi features values for different problems of LPs unlike the pre-processing algorithms (Lee, Han, & Ko, 2013; Patel, Shah, & Patel, 2013; Silapachote, Karupiah, & Hanson, 2005). The third stage is to segment the LP area and extract the characters by using many techniques, such as projecting color information, labeling, or matching positions with templates. The final stage is to recognize the LP extracted characters by using template matching or using classifiers, such as boosting, extreme learning machine, neural networks and fuzzy classifiers (Baharlou et al., 2015; Chakraborty & Parekh, 2015; Han, Lee, Lim, & Chung, 2015). This stage needs many Samples of characters as inputs for training in advance. Then, the input image of segment characters is compared with the trained data to produce the output results. There are many surveys have been conducted by many authors (Atiwadkar, Mahajan, Lande, & Patil, 2015; Bhardwaj & Mahajan, 2015; Du, Ibrahim, Shehata, & Badawy, 2013; Panchal, Patel, & Panchal, 2016; Patel et al., 2013; M. Sarker, Mostafa, Yoon, Lee, & Park, 2013) related on ALPR system problems which are affected on detection and recognition stages:

- i Low resolution problems related with camera quality and the distance between vehicle and camera.
- ii Plate problems such as blurry, location, sizes, special symbols and fonts, occlusion, tilted, blurry LP backgrounds, distortions, and screws.
- iii Environmental problems, such as lighting, rainy day, snow.
- iv Illumination problems, such as vehicle headlights, and different lighting sources during image capturing.

In the past and recently time, many efforts have been done to develop a robust LPD system, but they missed most of LPs issues which make the LPD systems very limited for detecting LP level. Therefore, an efficient LP detection method is still needed to make a robust LPD system. In this paper, we focus only on the LP detection area from a vehicle image, so we not consider the segmentation and recognition stages of an ANPR system. The main objective of this study is to develop a LPD method that yields better performance for vehicles images having different difficult conditions, such as low/high contrast, dusk, foggy, and distorted. It employed a large number of AdaBoost cascades classifiers with three-levels LBPs (3L-LBP) features to detect the ROI area for LP from vehicles images. The paper is organized as follows: The first section introduces the ANPR system. The second section

provides an overview of the related work about ANPR systems. Section 3 presents the proposed method. The experimental results are reported in Section 4. Finally, this study is concluded with some useful recommendations and suggestions for the future work.

2. Related work

Over the years, there are many algorithms being developed to extract LP features from one image or a sequence of images (video). Those features are used as the input to various classifiers such as cascade classifier, neural networks and fuzzy logic classifiers (Du et al., 2013). Different features, such as Haar-like feature, LBP features, ROI features, color features, boundary features, edge features and texture feature (Anagnostopoulos, Anagnostopoulos, Psoroulas, Loumos, & Kayafas, 2008; Azad, Davami, Jeo, & Shayegh, 2014; He, Zhang, Jia, Wu, & Hintz, 2007; Jia, Zhang, & He, 2007; Zheng, Zhao, Gu, & Hu, 2012), are used either separately or combined together to detect the LP region from images. In this paper the proposed method uses ensemble of AdaBoost cascades of 3L-LBPs classifiers for extracting ROI features from the LP area. It is usually one AdaBoost cascade being employed to detect the LP area. Throughout our literature review, many methods for the LP detection have been developed for real time LPDs (Gao & Lee, 2015; Li & Shen, 2016; Lienhart & Maydt, 2002; Porikli & Kocak, 2006; Sarker & Song, 2014; Song & Sarker, 2014). A brief overview about those existing methods is discussed below.

A strong classifier reported by Viola and Jones (2004) was trained using an AdaBoost algorithm and Haar-like features. It performed well for face detection. The study used “integral image” to calculate Haar-like features and used the AdaBoost algorithm to reduce the Haar-like features, and trained one cascaded classifier. The cascade classifier involved several stages to discard unwanted regions (non-face) from the image and saved the interested regions (face) for future processing. The accuracy rate by that algorithm was 96%. Ho, Lim, and Tay (2009) used two stages methods to extract the LP features. Several LP regions were identified in the first stage using a gentle AdaBoost classifier. In the second stage, the false positive rate was filtered using a support vector machine (SVM) classifier based on a scale-invariant feature transform (SIFT). The accuracy rate for the LP detection was 92%. A principal visual word (PVW) technique was developed by Zhou, Li, Lu, and Tian (2012) to locate the LP by local feature matching together with the PVW. The accuracy rate for the LP detection was 84.8%. Lim and Tay (2010) designed a character based method, maximally stable extremely regions (MSER) method to detect char-

Download English Version:

<https://daneshyari.com/en/article/4943011>

Download Persian Version:

<https://daneshyari.com/article/4943011>

[Daneshyari.com](https://daneshyari.com)