AUTOMATIC DETECTION OF LICENSE PLATE

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***Abstract*-Automatic detection of license plate (DLP) plays an important key role in numerous applications and a number of techniques have been proposed. License plate is detected in open environment such as background clutter, various observation angles, scale changes, multiple plates, uneven illumination, and so on. The proposed scheme uses the method principal visual word (PVW), discovery and local feature matching. PVW uses the idea of Bag Of Words (BOW) model but instead of applying to each character it uses the PVW characterized with geometric context. Given an image, the license plates are extracted by matching local features with PVW. Besides license plate detection, our approach can also be extended to the detection of logos and trademarks.**

Keywords- **principal visual word (PVW), clustering, geometric context, object detection**.

I. INTRODUCTION

Automatic detection of license plays a key role in intelligent transportation systems. It can be applied in vehicle management, such as security control, traffic monitoring, automatic vehicle or toll ticketing and so on.

Detecting the License plate is widely considered a solved problem, with many systems already in operation. The existing algorithms or systems work well only under some controlled conditions such as some systems require complex video capture hardware, possibly combined with infrared strobe lights, or require that the images be taken with little distortion from view-point changes. Although many reported results are very good, with even perfect accuracy on their test datasets, it is still a challenging task to detect license plates in open environment.

Typically, a DLP process consists of two main stages: 1) locating license plates and 2) identifying license numbers. In first stage it has to solve two problems: where a license plate is located and how big it is. Usually, to solve this, the candidate position of characters in the license plate is first identified, and the bounding box of the license plate is determined later.

Observing the specific character in different license plates and by using the idea of BOW model, the visual words are collected and generated from unsupervised clustering are sensitive to noisy features from image background; it is desirable to yield the principal visual words that correspond to each unique character in the license plate. Besides, these principal visual words PVW) are expected to contain geometric context, which can be used to deduce the size of the corresponding character. It also reduces the duplicate of license plate.

For each character we collect SIFT features falling into the character region and generate PVW by unsupervised Clustering are sensitive to noisy features from background image. The amount of PVW for each plate character is determined automatically. Each visual word contains some Geometric information, such as orientation, ratio of scale to character height, and relative position in the character region. Those geometric clues will be used to filter false feature matches and estimate the character and plate size. Due to the invariance of SIFT feature, our method can adaptively deal with various changes of license plate, such as distortion from observation views, scaling, and illumination. Multiple license plates in a single image can also be automatically detected. Based on matching with the PVW, we can accurately locate the image patch containing license plate.

In traditional many license plate detection algorithms have been proposed. Although license plate detection has been studied for many years, it is still a challenging task to detect license plates from different angles, partial occlusion, or multiple instances.

License plate detection has an input image to identify some local patches containing license plates. Since a plate can exist anywhere in an image with various sizes, it is infeasible to check every pixel to locate it. Generally, it is preferable to extract some features from images and focus only on those pixels characterized by the license plate. Based on the involved features, traditional license plate detection methods can be classified into three categories: color-based, edge-based, and texture-based.

Color based approach is based on observing the colors in the image. It extracts the license plate by locating their colors in the image. Extracting the license plate using color information has the advantage of detecting inclined and deformed plates. However, it will be very sensitive to various illumination changes and suffer from false positive especially when other parts of testing images have the same license plate color.

Edge based approach are most popular method, by extracting the license plate based on edge statistics. Although edge-based methods are reliable in many cases, it may be distracted by some objects with rich texture and similar shape. Besides, when license plates undergo changes from observation, edge based methods may partially detect or miss them.

Texture based approach are employed with neural network to detect the license plate. Using the Haar-like features that are invariant to brightness, color, size, and position of license plates. However, in open environment, license plates may undergo changes from rotation and observation views, and it is difficult to obtain enough comprehensive samples to cover such variations.

Distinguished from the above method, our approach is motivated from the BOW model based on local invariant feature. Thus our model uses a principal visual word (PVW) with geometric clues and it also uses the properties of local SIFT features to identify the license plate more accurately.

II. NEW APPROACH

The framework of our approach consists of three key components: PVW generation, visual word matching, and license plate location.

A.PVW generation

Generation of PVW is from a number of characters that are exit in all license plates are sorted, each with the same format, but maybe undergo some illumination changes or affine transformation. Since SIFT features are invariant to changes in scale and rotation, and also robust to illumination change and affine distortion, some distinctive and repeatable SIFT features exist, called PVW.

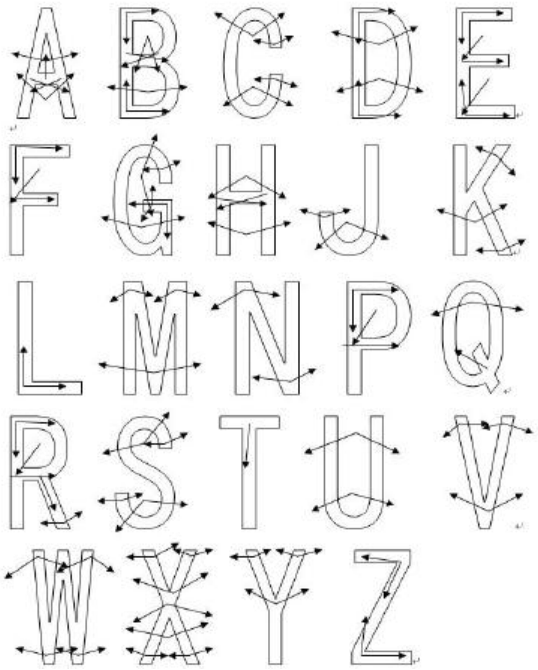


Fig.1 PVW of each letter.

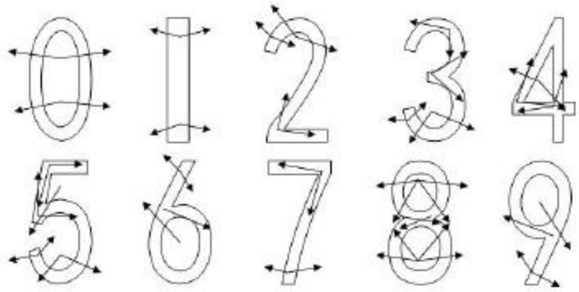


Fig.2 PVW of each digit

PVW is denoted as V (des, ori, rat, pos), where des is SIFT descriptor, ori is the SIFT orientation, rat is height scale ratio, and pos is a position of the character region.

We collect many images, each containing one or more license plates with little affine distortion. Each character in the license plate is annotated and all SIFT features in each character region are extracted. Usually, many noisy features also exist. To discover the PVW of each character, we need to cluster the local features of each character and discover the most representative cluster centers as the PVW.

Clustering is performed by means of affine propagation. The most important merit of affinity propagation is that it does not need to pre-specify the cluster number, which can be found automatically in the clustering process. In affinity propagation, a similarity matrix of samples shall be defined. It first gives the distance metric, which will be used to define the similarity metric.

Distance metric is the distance between the two local features which is the distance of descriptor, orientation, height scale ratio, and position. The similarity metric is a decreasing function of the distance metric.
In affinity propagation, the diagonal elements in the similarity matrix are referred to as exemplar preference, which will influence the number of identified clusters. After clustering, we need to discover the most representative clusters. For each cluster, we count the number of image patches which contain at least one feature falling into the cluster. Then an image-number histogram is built. To select those representative clusters, a threshold thresh shall be specified on the histogram. Any cluster with image number above thresh will be selected. In each selected cluster, the PVW are defined as the average of all samples falling into that cluster. Here we are using thresh=0.6.num where num is total sample number for a specific character. The PVW of characters from "0" to "9" are shown in Fig.1, while those of characters from "A" to "Z" excluding "I" and "O". The PVW of each digit are shown in the Fig.2.

B.Visual word matching

Given a test image, we will discover those characters with features matched to the PVW. We first extract SIFT features from the test image. Then each SIFT feature *F* (des, ori, scl) is compared with the PVW of each character. A feature is considered as a candidate match if the minimum descriptor distance to a PVW of a certain character is less than a constant threshold T (T = 0.5).

Each candidate match is recorded as C(x, y, angle, height, pos), where x and y are the position of the test SIFT feature in the image plane, angle is the rotation from the test feature to the matched visual word, height is the estimated height of the corresponding license plate, pos is the relative position of the character.

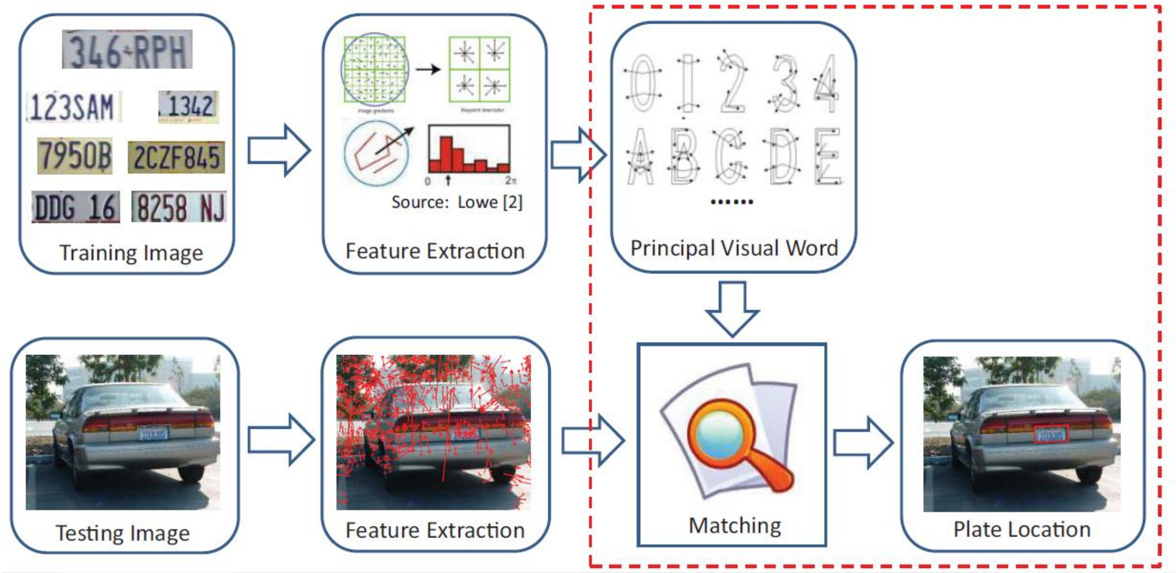


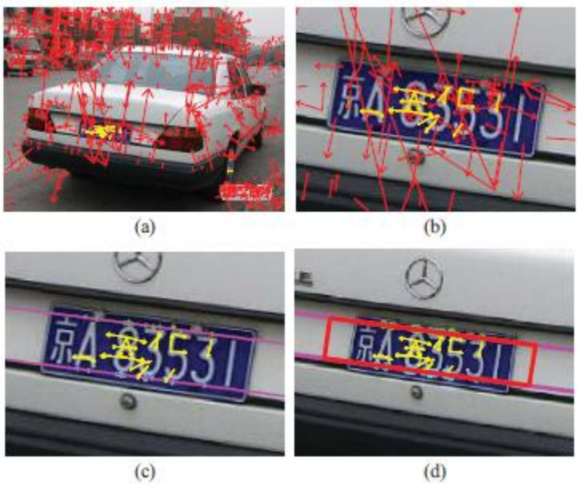
Fig.3 framework of license plate detection.

In some cases, multiple license plates may exist in one image, for that the character features located in the plate must be close to each other with distance less than the plate width, which is derived from the estimated plate height of each character feature. Based on this observation, clustering can be performed on the locations of matched features in an incremental way. Matched features of each cluster correspond to a candidate license plate. Before locating the plate, false positive matches can be filtered based on consistency of orientation difference and estimated plate height.

The consistency of orientation difference can help to remove false positives. For all candidate features, a histogram of the orientation difference angle for all candidate matches is constructed. False positive candidate will be removed if its orientation difference is far away from the histogram peak. Similar operation can also be performed in the estimated plate heights for the remaining candidate matches to further remove false positives.

B.License plate locating

Once the character features in the test image are identified, we can make use of the geometric context of the matched PVW to locate the license plate. A bounding box will be estimated to encompass the license plate by determining the upper, lower, left, and right bounding lines sequentially. First, the upper and lower bounding box lines are estimated by linear regression and then roughly estimate the left and right bounding lines. In the license plate, the ratio of width to height of the plate is constant. Thus when the plate height is estimated we can obtain the width of the license plate.



(a) SIFT feature detected from the image. (b)Identified character features of interest in yellow. (c) detected upper and lower bounding lines (d) detected the license plate in red.

sThe bounding box will also contain some background patch and it is removed by the information edge map. Thus the license plate is detected accurately with minimum false detecting rate.

III. EXPERIMENTAL RESULTS

Different testing license plate images are collected which may include many confusing elements, such as road signs, written advertisements, logos, cluttered background, etc. Using our approach it is tested to detect the license plate. The result gives 93.2% detection rate.

The performance is evaluated and the false positive rate is 1.0% which is less than the existing system. The false positive rate is defined as the ratio of false detection results to the number of detection results. The detection result of our approach is higher and more accurate and efficient.

This approach is more robust to background noise, blur, partial occlusion, low resolution, etc. It can also detect the multiple license plates automatically.

IV CONCLUSION

In this paper, we proposed an automatic approach for license plate detection in open Environment. Our approach is based on PVW discovering and visual word matching. We identify the PVW of each character. With the invariance merit of SIFT feature, our approach is effective in dealing with various observation angles, scale change, and illumination variation, etc. Besides, our approach can detect multiple plates in an image automatically.

The weakness of our approach is that it may fail when the license plate resolution is too low, or when the distortion from the observation angle is too severe. This is because these two conditions make it difficult to detect the SIFT features matching the PVW of related characters.

In our future work we can substitute SIFT by other feature such as SURF, which is much more efficient in implementation than SIFT. We will also test other local affine invariant features, to better address severe affine distortion of license plate.

We will also explore the potential of our approach in detection of logos and trademarks.

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