Vehicle Type Identification Based on Car Tail Text Information

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***Abstract*—Based on feature matching of car tail text information, a novel approach for vehicle identification is proposed in this paper. Our method creatively implements Scale-Invariant Feature Transform (SIFT) to extract distinctive invariant features from car tail text sub-images, which is a new application of SIFT. In our approach, firstly, the coordinate and the content of a vehicle's license plate are presented during the process of plate localization and recognition. Secondly, based on the plate location information, we apply a text information localization procedure which could be divided into two processes, robust localization and accurate localization. Then, a SIFT-based template matching method is provided to recognize the text information. Finally, we are able to determine whether the result conforms to the known vehicle type captured according to the plate license contents in the vehicles information file. The experimental results show a high recognition rate in acceptable time and prove the availability of vehicle type identification.**

Keywords-Scale-Invariant Feature Transform; vehicle type identification; car tail text information; image matching

I. INTRODUCTION

The appearance of crimes that involve vehicles disrupts the usual traffic, public security and brought great potential safety hazard to the traffic, such as vehicle theft, and fake plate vehicles. Therefore, research on intelligent traffic management has both social and economic value. The Intelligent Transport System (ITS) based on computer vision has been referred in the literature quite frequently in recent years. Many subsystems of ITS have been developed and applied all over the world. Among those various subsystems, Vehicle Manufacturer Recognition (VMR) is a crucial subject, but also rather difficult task. Currently, license plate recognition technology is widely applied in ITSs and quite matures in some ways. What's more, systems which are exclusively based on automatic license plate or logo detection and recognition lost sight of the car tail text information detection and recognition. However, it is still an open field to work due to complexity of vehicle information and imaging conditions.

As a symbol of the car manufacturer, vehicle's logo has attracted lots of attention, and methods have already presented in existing literatures [1, 2]. In addition, there's more information which could be elicited at the rear of the car, such as the specific model and displacement of a car. There are a lot of research about the vehicle license plate and logo, whereas very few people do enough work on the detail information mentioned above.

The principal work for car tail text identification is feature matching, which is also a difficult task. To identify correspondences between two images is an important task in the computer vision; these applications include object recognition, gesture recognition, image stitching, object tracking and industrial inspection. Choosing efficient features is the initial step to reliably perform that task, even under complicated shooting situations and geometric transformations. One of the most commonly used methods to extract and represent features is SIFT, which is invariant to image rotation and scale and robust across a substantial range of affine distortion, addition of noise, and partially invariant to changes in illumination.

In this paper, a new method of vehicle type validation based on text information of car tail is proposed. The proposed method uses Scale-Invariant Feature Transforms to represent the text and is more robust than other image features, such as Hu Invariant Moment proposed by Hu [3] in 1962 and Corner Detector by Harris and Stephens [4] in 1988, when treating the complex characters, like Chinese characters. The proposed algorithm is shown to be effective and efficient, which demonstrates excellent performance on a representative and typical database collected from the real world.

The rest of this paper is organized as follows. Section II sets out the latest development and research on vehicle identification and feature matching. In Section III, we present the overall framework for vehicle type identification in our work. Section IV shows the experimental results of the system process. By testing hundreds of texts captured from rear-view images, the results show that the proposed method has a good recognition effect. Finally, the paper is concluded in Section V.

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II. RELATED WORK

Many vehicle type identification methods have been applied nowadays. Among those frequently used tasks, varies of technologies have been applied. These methods have been proposed to recognize the vehicle manufacturer and model from frontal or rear views of vehicles. Vehicles are identified by extracting features, and then matching these features as templates or as a machine learning problem. The detection and matching of interest points serve as the basis for many computer vision applications; including image/video retrieval, object categorization and recognition, and 3-D scene reconstruction. A wide variety of detectors and descriptors have already been proposed in the existing literature.

The development of image matching by using local features can be traced back to the work of Moravec [5] on stereo matching using a corner detector in 1981. In 1988, Harris and Stephens improved the Moravec detector to make it more repeatable under small image variations and near edges. Harris also showed its value for efficient motion tracking and 3D structure from motion recovery [6], and the Harris corner detector has since been widely used for many other image matching tasks. These feature detectors called corner detectors are not selecting just corners, but rather an image localization that has large gradients in all directions on a predetermined scale. The Harris corner detector is very sensitive to changes in image scale, so it does not offer a good basis for matching images of different sizes.

The ground-breaking work of Lowe and Brown [7-9] showed that SIFT could extend the local feature approach to achieve scale invariance. They also described a local descriptor with more distinctive features while being less sensitive to image distortion such as translation, rotation, scaling or any combination of these. They proposed a method to use groups of interest points to compute local 2D transformation parameters. By using these different points they form the feature descriptors which are invariant to any 2D projective transformation. As to feature matching, they identify matching key from the new images, Beis and Lowe used a modification of the k-d tree algorithm called the Best-bin-first search method [10] that can identify the nearest neighbors with high probability using only a limited amount of computation. In addition to enabling robust matching, they present a scheme that each match represents a hypothesis of the local 2D transformation. Then Ballard use broad-bin Hough transform clustering [11] to select matches that could also reject outliers.

Because of the variations in the visual appearances vehicle types, developing a highly accurate vehicle recognition system in applications is still very challenging. Most recently published papers have primarily classified vehicles into different types for control of traffic flow. For example, Dlagnekov [12] used a license plate detector to define a vehicle ROI and then a SIFT matching scheme to retrieve desired vehicle recognition system. Zafar et al. [13] used a contourlet transform to extract vehicle features and then applied a 2-D linear discriminant analysis for dimensionality reduction, achieving a VMR system. Hsieh et al. [14] proposed a Symmetrical SURF (Speeded-Up Robust Features) and its application to vehicle make and model recognition based on the front view of vehicles. The method based on vehicle type identification was proposed by [15], they use SIFT to extract global and local features from the front-view or rear-view images of vehicles. However, this method does not have good recognition accuracy between similar types of vehicles.

The above methods are all related to the vehicle logo or the vehicle face, but the vehicles with the same logo or face shape perhaps have different manufacturers, models or swept volume, most of these information though are distributed on the car tail, due to the lack of the uniform standard, it becomes quiet difficult to identify these text information. The traditional character recognition methods have been presented in the past years [16-19]. Nevertheless, these methods should have the separate characters first, in a practical application, because of the complex environment, most characters with deformation, conglutination and blurring affect character segmentation directly, and what's more, the text information captured from vehicle images usually within even small area, all these causes led to traditional character recognition methods' limitation in vehicle text information recognition.

The most related work to ours is SIFT proposed by David Lowe. We described a SIFT-based vehicle car tail text information feature matching schema, whose aim is to obtain vehicle type from car tail text information captured in the rear-view vehicle images. The SIFT matching module detects and extracts keypoints in the text sub-images that are located and segmented from the source images, describes them and matches them with keypoints stored in a sample image database. Then the process is optimized by clustering the matched keypoints. The proposed method is assessed on a training set(database) containing 200 text sub-images, using a testing set containing 1200 query images.

III. PROPOSED APPROACH

The proposed vehicle type identification (VTI) method mainly has two stages: training and classification. In the training stage, car tail text samples are collected from vehicle rear-view images of common models. Then, SIFT features are extracted from all samples. Next, feature representation is built for each sample, and is organized with the image's path into the training set. The classification stage consists of three main parts: (1) license plate recognition, (2) text area localization, (3) text information matching, and the part (2) could be divided into two sub-tasks: robust test area localization and accurate test area localization.

In this section, we discuss parts (2) and (3) in details, and for the completeness, we briefly describe part (1), which mainly follows previous work in [3, 12, 16]. In the first part, we locate the license plate area and then recognize the text content of the license plate to obtain the information of the vehicle, which has been collected in the known vehicle information file. Next, text area sub-images are intercepted from the query image by a priori knowledge. After that, SIFT features are extracted from each text area sub-image and match with the samples in the training set. The result shows whether the vehicle's model conforms to the known vehicle type that captured according to the plate license contents in the vehicles information file. The process flow diagram is shown in Fig. 1.

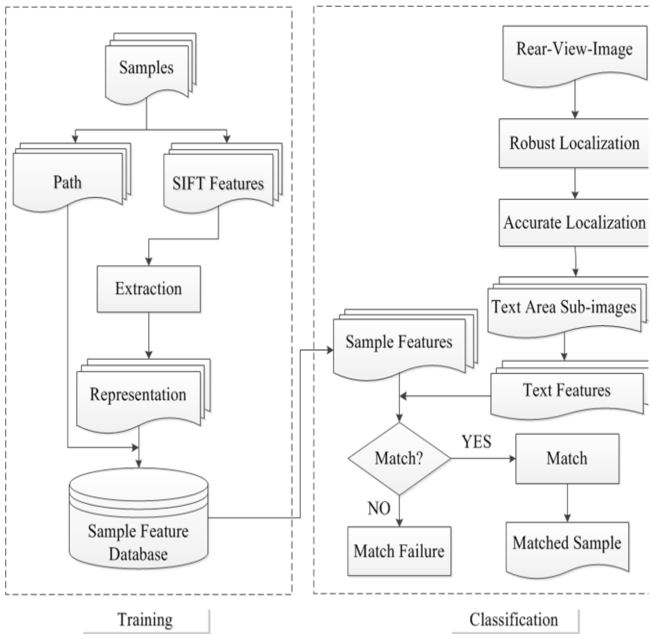

Figure 1. VTI system flowchart.

A. SIFT Feature Representation

Feature representation is the key issue of building a sample feature database, which distinguishes one query image from other samples. SIFT is the state-of-the-art in the field of image recognition and is used in a wide range of image retrieval applications. It exploits the idea of representing images by a set of scales and invariant keypoint descriptors using histograms of locally orientated gradients. The invariant features, or just keypoints, are detected and extracted, exploring the scale space of the image. Then the features are localized and filtered to preserve only those that are likely to remain stable over affine transformations. The process of extracting features for a SIFT keypoint descriptor encompasses four stages.

1) Detection of scale-space extrema: in this stage, Lowe [8] using the extrema in the Difference-of-Gaussian (DoG) function convolved with the image. Then all the images are detected by comparing a pixel (marked with X) to its 26 neighbors in 3×3 regions at the current and adjacent scales. Pixel is chosen as a keypoint if its value is either minimum or maximum.

2) Accurate keypoint localization: rejecting keypoints with low contrast (sensitive to noise) or are poorly localized along an edge (DoG operator has high edge responses) to provide an improvement to matching and stability.

3) Orientation assignment: assigning a consistent orientation to each keypoint to make sure the property of rotation invariance.

4) Descriptor assignment: parameters (image location, scale and orientation to each keypoint) that have been assigned by previous operations impose a repeatable local 2D coordinate system in which to describe the local image region. Therefore, the next step is to compute a descriptor for the local image region. Finally, a rotation-invariant descriptor called SIFT, which computes a histogram of locally oriented gradients around the interest point and stores the bins in a 128-D vector.

B. Feature Matching Scheme

For each feature i in the query images, SIFT matching scheme is applied on finding its Nearest-Neighbor (NN) matches among all the features stored from images j in a database. The nearest neighbor is defined as the keypoint with minimum Euclidean distance for the invariant descriptor vector:

$$NN_i = cardinality\{arg[\| Q_i - D_i(j) \| < \gamma]\} \quad (1)$$

Where Q_i is the i^{th} descriptor for the query image, D_i(j) is the i^{th} descriptor for the j^{th} image in the database and γ is an appropriate threshold value. The selection of threshold (γ) directly impacts the numbers of NNs in the database for each feature (keypoint). In Fig. 2, the parameter (δ) is plotted versus threshold (γ) , where δ is described by (2):

$$\delta = \frac{NN_i}{KP_Q * KP_D} \quad (2)$$

Where NN_i is calculated from (1) for each feature i in the query image. KP_Q is the number of keypoints detected from the query image, and KP_D is the number of the keypoints in the database.

The keypoint descriptor has a 128-dimensional feature vector, therefore, an algorithm [10] similar to k-d tree (Friedman et al. [20]) called the Best-Bin-First (BBF) are used in the matching scheme to speed up search. In the implementation, we cut off search after checking the first 200 NN candidates. It returns the closest neighbor with high probability over a reasonable time frame.

There are 200 samples in the database, and each sample has about 500 or more keypoints, numbers of which may not important to the match stage. To discard more false matches arising from the background, Nearest Neighbor features are clustered using the Hough Transform [21, 22], and in order to

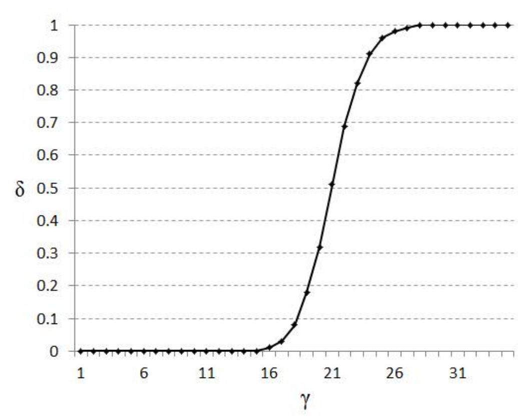

Figure 2. Reduced Nearest Neighbor parameter (δ) plotted versus distance threshold (γ).

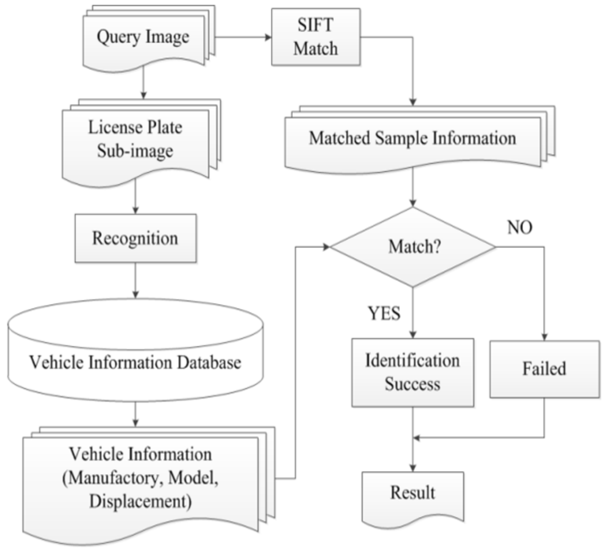

Figure 3. The verification process flowchart.

define the parameters for a similarity transformation between the query and database features. The Hough Transform identifies clusters of features with a consistent transform representation (2D location, scale, orientation and a record of the keypoints' parameters relative to the matched sample) by using each feature to vote for all the sample images that are consistent with the feature. When the clusters of the features are found to vote the same pose of the sample, the matched sample has a higher probability of the correct one than any other feature. The one which has the highest votes in the database is considered as the most possible matched result of the query image.

After previous tasks, clusters that are identified by Hough Transform are then entrance a new procedure to keep stability of geometric transformation. The affine transformation of a model point $[x, y]^T$ to a query point $[u, v]^T$ should satisfy the matrix relationship shown in (3):

$$\begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} p_1 & p_2 \\ p_3 & p_4 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} t_x \\ t_y \end{pmatrix} \tag{3}$$

Where $[t_x, t_y]^T$ is the translation value of the similarity transformation, and $p_i (i = 1,2,3,4)$ are the affine rotation, scale, and stretch parameters. Because we wish to get the transformation vector, so (3) could be rewritten to the matrix shown in (4):

$$\begin{pmatrix} u \\ v \\ \vdots \end{pmatrix} = \begin{pmatrix} x & y & 0 & 0 & 1 & 0 \\ 0 & 0 & x & y & 0 & 1 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{pmatrix} \begin{pmatrix} p_1 \\ p_2 \\ p_3 \\ p_4 \\ t_x \\ t_y \end{pmatrix} \tag{4}$$

If (4) is considered as a system of $A * x = B$, then the parameter x can be determined by the following equation:

Figure 4. Successful license plate detection and characters segmentation result.

$$x = [A^T A]^{-1} A^T B \tag{5}$$

Then, the RANSAC method [23] is applied for all Hough Transform clusters found, and the affine transformation with the maximum number of inliers (or minimum number of outliers) is estimated. Lowe [7] reports that it is possible to have reliable recognition with as few as three feature correct matches.

C. *License Plate Recognition*

The first task for the proposed VTI system is capturing the vehicle's information, and then comes the verification process; the matching process is shown in Fig. 3. In the rear-view vehicle image, the license plate region is steady-going and fixed in size [24]. Based on this property, the number plate can be fast and robust detected, then the characters on the license plate can be segmented into individual ones, as showed in Fig. 4. Next, combined features [16, 18, 19, 25] would be captured for accurate localization and character recognition. There are many methods of vehicle license plate localization and recognition that have been presented in existing literature [24-27] as yet, and need not be repeated here.

D. *Text Area Detection*

The license plate is located, and using their position and size, it can also be obtained from the text areas on the car tail. The accuracy of the text area segmentation will directly affect the matching result. We segment the sub-images using a method which combines a prior knowledge with brim characteristic.

1) Robust Text Area Localization

Using the license plate location and size, a robust text area could be located. Based on the priori knowledge, we know that the text area is mostly located at the car trunk and beside the taillights. As is shown in Fig. 5, positions of the ROI could be obtained.

Based on the experience, the text area could be located for the most part follow the equation:

$$\begin{cases} l_l.x = rect.x - te * \Delta w \\ l_r.x = rect.x \\ l_t.y = rect.y - ts * \Delta h \\ l_b.y = rect.y - te * \Delta h \end{cases} \tag{6}$$

Where $(l_l.x, l_t.y)$ is coordinate of the upper left corner of the left text area sub-image, $(l_r.x, l_b.y)$ is coordinate of the lower right corner of the left text area sub-image, and te, ts are normalization coefficient in order to achieve a reasonable position for the text area (default $te = 1$, $ts = 2$). The right

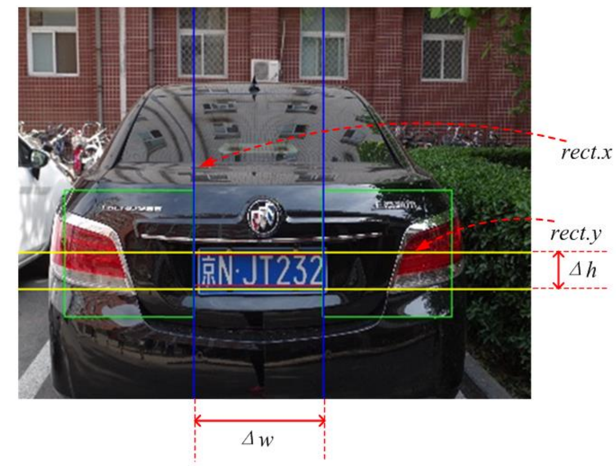

Figure 5. Notations for finding the upper and bottom boundaries of ROI for robust text areas. The parameters *rect.x* and *rect.y* are the left or top of the license plate, Δw and Δh are the width, height.

text area sub-image corresponds to a similar law, and it is no need to spell out.

2) Accurate Text Area Localization

After detecting the ROI, robust text areas have been segmented, the next step is detecting text in the ROI images. Most of the available methods for text detecting use gray-scale or binary images, because methods for color analysis are time-consuming or involve elaborate processing. After image preprocessing, we using edge detection and projection to detect the text area (an edge in gray-level images is changed suddenly in value from white to black). Projection is a favored algorithm for text detection; it is based on alterations of edges in limited areas. Our method uses horizontal projection to find the candidate regions (see Fig.6 (a)). Then candidates screening is implemented by threshold processing by the following equation:

$$p(y) = \begin{cases} 0 & if \;\; p(y) < T \\ p(y) & if \;\; P(y) \geq T \end{cases} \tag{7}$$

Where p(y) is the horizontal projection image, and T is threshold value which is obtained by empirical knowledge.

The upper and lower boundaries of the text region can be determined after the threshold processing (see Fig.6 (b)). Similarly, the left and right boundaries of the text region can be confirmed (see Fig.6(c)).

IV. Experiments and Results

An automatic system for vehicle type identification based on car tail text information was implemented in this paper to evaluate the performance of our system. The process of license plate recognition has been completed by previous work, no need to display the experimental results here.

Twenty-five vehicle types are collected in the paper for performance evaluation, and they are the most common models of all, such as Toyota Camry, Toyota Vios, Honda CRV, Nissan Tenna, Ford Mondeo, Benz C200, etc. To train the SIFT classifier, a database containing 200 text information classes of the car tail were collected, which contains color images with image sizes varying from 215×85 to 1005×650. Fig. 7 shows some of the samples. The text information of the car tail usually contains three parts: manufactory, model and displacement. In mostly literatures for vehicle recognition or model verification, they use vehicle logo to recognize the vehicle type, it maybe causes information loss.

For the testing set, we test the method with sets of images (size: 1200×900 pixels) taken by PENTAX K-50 camera, while 1200 sub-images from 684 rear-view vehicle images are captured after text area localization processing. The testing images are all captured without making any controlled condition; the system is close to the real environment. It encompasses 25 categories of vehicles under sunny, cloudy, backlighting or shadow conditions.

In our system, we have considered as much information as possible; consequently, the vehicle type matching is designed to guarantee uniqueness. Firstly, the query image is divided into two or three parts: including information about the vehicle manufacturer, model and displacement; after that, the three sorts of information matching with samples which stored in the database respectively; ultimately the result could be obtained. In the existing methods, the usual plans are matching vehicle logo or vehicle face; while various vehicle types may have similar face or the same logo, it is hard to differentiate between the query one from others. Our method has improved this current situation.

In Section II, we have demonstrated the vehicle text area detection and segmentation, and the result has shown in Fig.6. Firstly, we capture the region of interest by a prior knowledge as is shown in Fig.5, after segmenting the ROI, accurate localization processing operates for obtaining the sub-image that used up to matching scheme. We use a serious of pre-processing procedures (image smoothing, edge extraction and binaryzation) to enhance image information. Next, the statistical law of the characters of car tail text area horizontal projection is used to select in the ROI of the text area and determine the top and bottom borders. As Fig.6 shows, the text area presents a higher peak value. What's more, the vertical

(a)

(b)

(c)

Figure 6. (a)ROI sub-image after robust localization and its horizontal projection. (b)Vertical projection of the text area sub-image. (c).Accurate localization result.

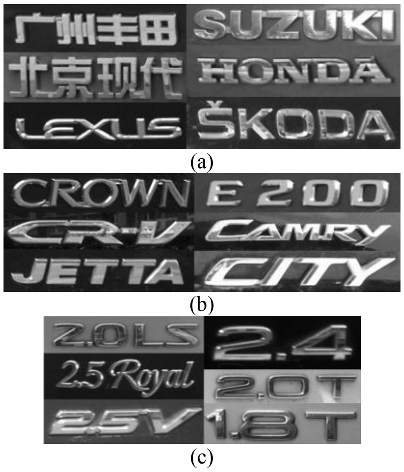

Figure 7. (a) Samples of manufactory information. (b) Samples of model information. (c) Samples of displacement information.

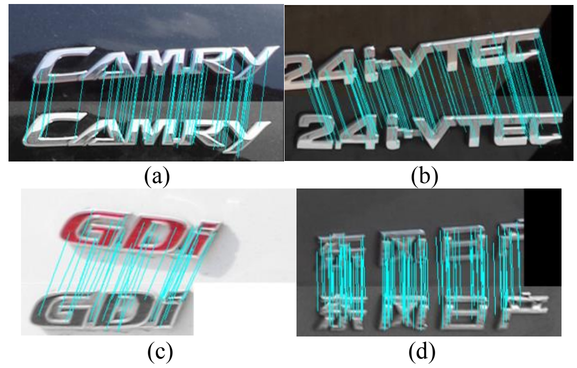

Fig.8 Results of the text recognition. The upper images are text sub-images which are segmented from the query images (from training set) after text localization processing, and lower ones are samples from the database. Query images are in a RGB color format, while sample images are all in grayscale.

projection shows continuous projection imaging. So we can determine the right and left borders. Computation, nature of performance of text-segmentation process is 88% on average. The detection process requires about 420 ms.

Fig. 8 shows some successful results. The results suggest that our system is robust against large variations in color, size, geometric distortion and even some local defect. Lines connect the matched features between the query image and a sample image. A successful match occurs when the two keypoints correspond to the same location and a failed match when two keypoints come from different locations. These parallel lines ensure the good matching effect, while several amorphous ones indicate they are wrong matching pairs. For different experimental conditions, we vary the threshold value (γ) .

We also give an indicative example of the NN matches to show the distinction between matched sample and the others. There are 158 keypoints (KP_s) have found in the query image, and matched feature number (NNs) has also been added up (see Fig. 9).

In order to ensure the accuracy of the matching results, it needs to not only minimum within-clusters, but also maximum between-clusters. As is shown in Fig.9, the correct match has the maximum amount of keypoints, while the false match has a small number. It could be also regarded as the similarity between the query image and sample images. The features and the matched points have been marked in Fig.9, though there are several matches in the unmatched samples, most of them are false ones.

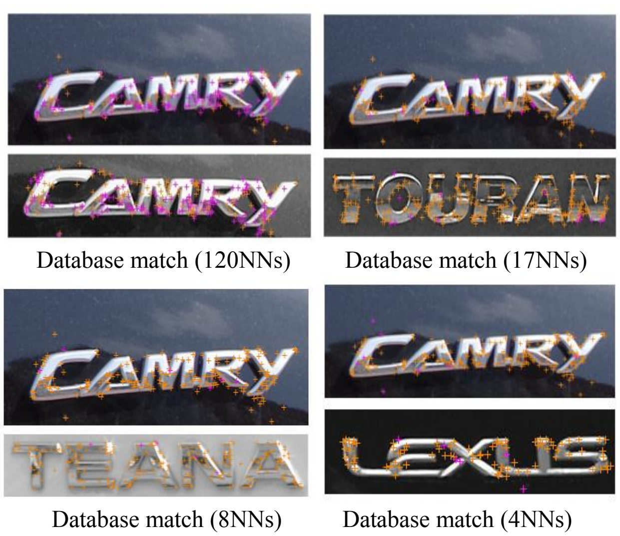

Figure 9. NN match for a sample query image.

Because of various numbers of keypoints can be captured from different query images, the accuracy of text recognition may be different either. In our experimentation, we test images with different sizes under various resolutions. As is shown in Fig. 10, one image of little features has a low recognition rate. So, SIFT-based algorithms require the original image to have a certain level of resolution; otherwise, the properties of the feature would not be stable when the image is scaled down. In our testing set and training set, the average number of images' keypoints is close to 150. The accuracy analysis of our text information recognition method is shown in Table I.

The recognition rate of the information is determined by its contents. Compared with manufacturer and model information, displacement information is simpler and mostly composed of

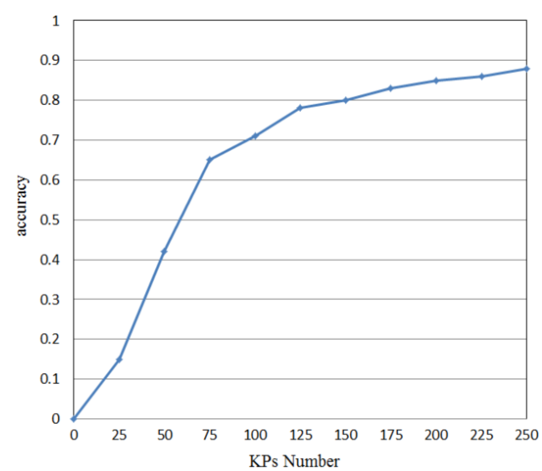

Figure 10. The polygonal line shows the accuracy of query images with various numbers of keypoints matched to a database.

TABLE I. EXPERIMENTAL RESULT FOR THE THREE SORTS OF INFORMATION

Query information	True	False	Total	Precision
Manufacturer	293	107	400	73.25%
Model	507	81	588	86.22%
Displacement	196	16	212	92.45%

figures and English letters, so it becomes the most easily part to recognize. For manufacturer information, the precision has the worst result by reason of many of the query sub-images including the content of Chinese characters. On the basis of the existing technology, it is hard to recognize for Chinese characters. In addition to weather, backlighting and shadow can also affect the performance of text area detection and recognition. And the worst false alarm is due to the influence of the shadow in the sunny days. Computation, the overall recognition success rate is 83%.

The VTI system has a high running speed, with a combined detection and recognition time of about 4.8 s (420 ms + 4.38 s) on average, which is suitable for applications. The recognition speed of the three sorts of information is shown for comparison in Table II. Once we get the matched vehicle information, a search on the vehicle information file will process, which costs approximately 180 ms.

TABLE II. VEHICLE TEXT INFORMATION RECOGNITION RATE

Query information	Time(second)
Manufacturer	5.89
Model	3.64
Displacement	3.62

V. CONCLUSION

In this paper, we have proposed a vehicle type identification system based on car tail text information, which is a new application for SIFT algorithm. By testing hundreds of the rear-view vehicle images, the results show that the proposed method has good efficiency. And the accuracy is still within “acceptable” limit.

Experimental results have proved the viability of our proposed system; however, there are still defects, such as lack of training samples, low precision rates in the Chinese characters recognition. Future work will focus on the improvement of SIFT to adapt to low-resolution images and to accurately recognize the Chinese characters.

REFERENCES

[1] A. P. Psyllos, C. N. E. Anagnostopoulos, and E. Kayafas, “Vehicle Logo Recognition Using a SIFT-Based Enhanced Matching Scheme,” IEEE Transactions on Intelligent Transportation System, Vol.11, No.2, pp. 322-328, 2010.

[2] A. P. Psyllos, C. N. E. Anagnostopoulos, and E. Kayafas, “M-SIFT: A New Method for Vehicle Logo Recognition,” IEEE International Conference on Vehicle Electronics and Safety, 2012, pp. 261-266.

[3] M. K. Hu, “Visual Pattern Recognition by Moment Invariants,” IEEE Transactions on Information Theory, Vol. 8, No. 2, pp.179–187, 1962.

[4] C. Harris and M. Stephens, “A Combined Corner and Edge Detector,” The 4th Alvey Vision Conference, Vol. 53, No. 3, 1988, pp. 147–151.

[5] H. P. Moravec, “Rover Visual Obstacle Avoidance”, International Joint Conference on Artifacial Intelligence, Vol. 3, No. 4, Vancouver, Canade, 1981, pp. 785-790.

[6] C. Harris, “Geometry from Visual Motion,” Active Vision, MIT Press, Cambridge, pp, 263-284, 1992.

[7] D. G. Lowe, “Object Recognition from Local Scale-invariant Features,” International Conference on Computer Vision, Corfu, Greece, 1999, pp. 1150-1157.

[8] D. G. Lowe, “Distinctive Image Features from Scale-invariant Keypoints,” International Journal of Computer Vision, Vol. 60, No. 2, pp. 91–110, 2004.

[9] M. Brown and D. G. Lowe, “Invariant Features from Interest Point Groups,” British Machine Vision Conference, 2002, pp. 253-262.

[10] J. S. Beis and D. G. Lowe, “Shape Indexing Using Approximate Nearest-neighbour Search in High-dimensional Spaces,” Conference on Computer Vision and Pattern Recognition, Puerto Rico, 1997, pp. 1000–1006.

[11] D. H. Ballard, “Generalizing the Hough Transform to Detect Arbitrary Shapes,” Pattern Recognition, Vol. 13, No. 81, pp. 111–122, 1981.

[12] L. Dlagnekov, Video-based Car Surveillance: License Plate Make and Model Recognition, Master Thesis, University of California at San Diego, 2005.

[13] I. Zafar, E. A. Edirisinghe, and B. S. Acar, “Localized Contourlet Features in Vehicle Make and Model Recognition,” Proc. SPIE 7251, Image Processing: Machine Vision Applications II, Vol. 7251, 2009.

[14] J. W. Hsieh, L. C. Chen, and D. Y. Chen “Symmetrical SURF and Its Applications to Vehicle Detection and Vehicle Make and Model Recognition,” IEEE Transactions on Intelligent Transportation System, Vol. 15, No. 1, pp. 6-20, 2014.

[15] U. Iqbal, S. W. Zamir, and M. H. Shahid, “Image Based Vehicle Type Identification,” International Conference on Information and Emerging Technologies , 2010, pp. 1-5.

[16] D. Trier, A. Jain, and T. Taxt, “Feature Extraction Methods for Character Recognition-A Survey,” Pattern Recognition, Vol. 29, No. 95, pp. 641-662, 1996.

[17] M. Bosker, “Omnidocument Technologies,” Proceedings of the IEEE, Vol. 80, No. 7, pp. 1066-1078, 1992.

[18] M. H. Glauberman, “Character Recognition for Business Machines,” Electronics, Vol.29, No.2, pp. 132-136, 1956.

[19] D. Shen and H. H. S. Ip, “Discriminative Wavelet Shape Descriptors for Recognition of 2D Pattern,” Pattern Recognition, Vol. 32, No. 98, pp. 151-165, 1999.

[20] J. H. Friedman, J. L. Bentley, and R. A. Finkel, “An Algorithm for Finding Bestmatches in Logarithmic Expected Time,” ACM Transactions on Mathematical Software, Vol.3, No.3, pp. 209–226, 1977.

[21] P. V. C. Hough, Method and Means for Recognizing Complex Patterns, U.S. Patent 3069654, 1962.

[22] E. Grimson, “Object Recognition by Computer: The Role of Geometric Constraints,” The MIT Press, Cambridge, MA, 1990.

[23] M. A. Fischler and R. C. Bolles, “Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography,” Communications of the ACM, Vol. 24, No. 6, pp. 381–395, 1981.

[24] M. Diligenti, M. Gori, M. Maggini, and E. Martineli, “Adaptive Graphical Pattern Recognition for the Classification of Company Logos,” Pattern Recognition, Vol. 34, No. 10, pp. 2049-2061, 2001.

[25] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, “Automatic License Plate Recognition (ALPR) A State-of-the-Art Review,” IEEE Transactions on Circuits and Systems for Video Technology, Vol. 23, No. 2, pp. 311-325, 2013.

[26] H. Sheng, C. Li, Q. Wen, and Z. Xiong, “Real-Time Anti-Interference Location of Vehicle License Plates Using High-Definition Video,” IEEE Intelligent Transportation Systems Magazine, Vol. 1, No. 4, pp. 17-23, 2009.

[27] G. S. Hsu, J. C. Chen, and Y. Z. Chung, “Application-Oriented License Plate Recognition,” IEEE Transactions on Vehicilar Technology, Vol. 62, No. 2, pp. 552-561, 2013.