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# COLOUR FAST-MATCH FOR PRECISE VEHICLE RETRIEVAL

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## ABSTRACT

The explosive growth of vehicles has increased the importance of intelligent traffic system. However, compared with face recognition, vehicle retrieval has not attracted the attention of researchers in vision community. Precise vehicle retrieval has always been a challenging task because it requires the retrieval of all vehicles with the same visual attributes from a large number of vehicles with subtle visual differences. To handle this, the authors propose to implement precise vehicle retrieval using an improved fast affine matching colour image retrieval method based on the features of annual inspection label area. Moreover, regional colour constant and hue and saturation feature are introduced to the proposed method so as to settle the illumination change problem in the real surveillance scene.

**Keywords:** image classification, image retrieval, image matching, feature extraction.

## INTRODUCTION

Nowadays, License plate has been one of the core research objects in the area of intelligent traffic systems for a long period of time [1]. However, license plates on vehicles are not always fully visible and not easy to recognise under certain situations. First of all, some surveillance cameras are not designed for license plate capturing, thus, plate recognition performance drops dramatically on images or video data captured by these cameras. Moreover, license plates are often easily occluded, removed or even faked in a large number of previous security events [2]. Therefore, vision-based vehicle retrieval has a great practical value in real-world surveillance applications. Specifically, vehicle retrieval is

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the problem of identifying the same vehicle across different surveillance camera views.

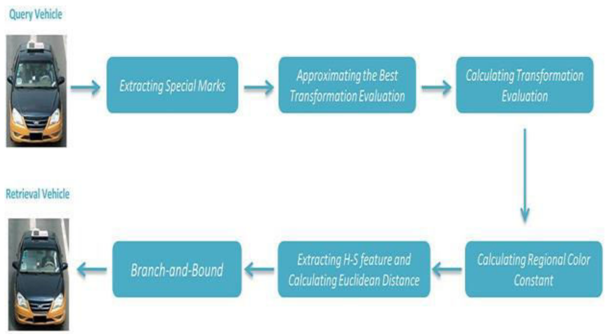


**Fig. 1** Flowchart of the proposed method

## LITERATURE RIVEW

In general, two core elements have influence on the accuracy of the vehicle retrieval problem, such as: how to extract features more effectively and to measure the distance between different image features more accurately. The method of image retrieval isgenerally divided into direct and feature-based types [9]. For the first one, the excellent work by Baker and Matthews [10], in which the minimisation of the sum of the squared differences between two images is obtained by seeking the parameter optical flow mapping between the images.

ASIFT [11] is a good example of a feature-based approach, which is designed to be affine invariant. However, these methods not perform well on fine-grained processing, such as accurate retrieval which requires information other than attribute tags. Fast-match [7] handles the explosion by properly discretising the 2D affine transformations space. Its assumption based on image smoothness is the most important improvement, that is, the number of potential transformations evaluated can be bounded. Our work mainly constructs a new vehicle retrieval system shown in Fig. 4, which is different from the above mentioned algorithms.Compared with above methods, the improvements are reflected by the following three aspects. Firstly, we train a deep network based on Faster-RCNN to make sure the vehicle retrieval system can detect vehicles from a particular surveillance video. Secondly, vehicle colour recognition [17] is taken as the coarse-grained feature extraction part in the proposed method. Last but not least, the most important improvement is that we are able to search the vehicle well at a fine-grained level, using a fast affine model matching method based on colour images, and combining the colour constants of special markers.

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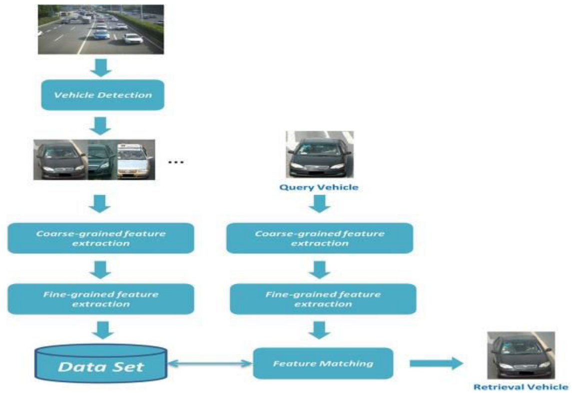


**Fig. 2** Flowchart of the vehicle retrieval system

Least, the most important improvement is that we are able to search the vehicle well at a fine-grained level, using a fast affine model matching method based on colour images, and combining the colour constants of special markers.

**Fig. 5** converting a colour image directly to grey scale images will resultin the loss of Colour information and so reduce the accuracy of matching

a fast affine model matching method based on colour images, and combining the colour constants of special markers.

**EXISTING METHOD**

This model consists of sensors to sense the presence of a vehicle, camera to capture the image, a motor with motor driver circuit to control the barrier on the entrance, PC on which algorithm is executed, and microcontroller for controlling the complete hardware of the ANPR system. As the vehicle enters and settles in the field of the sensor, the infrared sensor sense a vehicle and gives a signal to the PC through microcontroller 89C51 to capture the image of the vehicle. The camera connected to the PC through USB port captures the image of a vehicle. The ANPR algorithm on a PC receives the image and performs the processing, which yields the vehicle number.

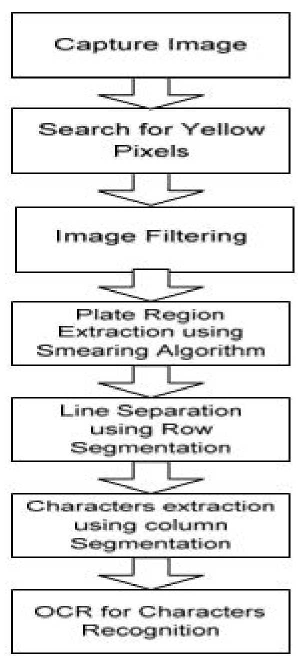


**Fig. 5** Steps of automatic number plate recognition model

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This number is then compared to the authorized number to confirm it validity and finally provides signal to microcontroller to control the system hardware. If the inputted plate contains the authorized number then the barrier on the entrance will be raised up using motor, green indication light will be switched on and 'Access Granted' will appears on the display, and if the inputted plate contains an unauthorized number then barrier will not be raised, red indication will be switched on and 'Access Denied' will appear on the display.

**PROPOSED METHOD**

In this work, we propose a fast colour matching method for accurate vehicle retrieval. Our algorithm can be mainly divided into five steps. Firstly, we extracted the annual inspection labels from the target vehicle image. Secondly, the labels are used to approximate the best transformation evaluation and the transformation evaluation is calculated then. Thirdly, we calculated the regional colour constant. Fourthly, we extracted the H–S feature from the labels. Last but not least, the branch-and-bound method is applied for the target vehicle retrieval.

3.1 Preliminaries and the best transformation evaluation

The annual inspection label $I_1$ is extracted from the query vehicle and regarded as the template ( while another annual inspection label $I_2$ is obtained from image in the dataset. As explained in [7], the method to measure similarity distance between $I_1$ and $I_2$ is as follows: $\Delta_T$ $I_1$, $I_2$ is the (normalised) sum-of-absolute-difference distance between template $I_1$ and image $I_2$, including a transformation $T$ that maps pixels $p \in I_1$ to pixels in $I_2$ [18]. Mathematical formulas can be described as

$$\Delta_T(I_1, I_2) = \frac{1}{n_1^2} \sum_{p \in I_1} \left\| I_1(p) - I_2(T(p)) \right\|, \qquad (1)$$

furthermore, when the input images $I_1$ and $I_2$ are coloured, they need to be converted to greyscale images. Therefore, formula (1) can be modified as

$$(I_1^R(p) - I_2^R(T(p))) \times 0.299 +$$

$$\Delta_T(I_1, I_2) = n\underline{1}_{12\,p}\sum_{\in I_1} \left\| (I(_{1G}I_1(_B p(p) - \right.$$

$$\left. - I_{2G} I_{2B}(T(T((pp))) \times 0.587 +))) \times 0.114 \right\|. \qquad (2)$$

colour difference between the image and the template in each channel, so formula (2) is modified as

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$$\Delta_T(I_1, I_2) \frac{1}{n_1^2} \sum_{p \in I_1} W(I_1(p), I_2(T(p))), \qquad (3$$

$$W(p) \left( \begin{array}{l} \left\| I_1^R(p) - I_2^R(T(p)) \right\| + \\ \left\| I_1^G(p) \quad I_2^G(T(p)) \right\| + \\ \left\| I_1^B(p) \quad I_2^B(T(p)) \right\| \end{array} \right) \times G(p), \qquad (4$$

where $\Delta G(p)$ is the difference coefficient between $p$ and $T(p)$. In addition, $\Delta G(p)$ can be calculated by Algorithm 1 (see Fig. 6).

$$L(T,T') = \max_{p \in I_1} \left\| T(p) - T'(p) \right\|_2 . \qquad (6)$$

$$W(p, T(p)) = \begin{cases} \left( \begin{array}{l} \left\| I_1^R(p) - I_2^R(T(p)) \right\| + \\ \left\| I_1^G(p) - I_2^G(T(p)) \right\| + \\ \left\| I_1^B(p) - I_2^B(T(p)) \right\| \end{array} \right) \times \Delta G(p), & p \in I_2 \\ 1, & p \notin I_2 \end{cases}$$

In the target image plane, $L(T,T')$ is the Euclidean distance between $T(p)$ and $T'(p)$. Particularly, this definition depends on the mappings $T$, $T'$ and the dimension of the source image $I_1$ rather than the pixel values of the images. Furthermore, we can bound the differences between $\Delta_T(I_1, I_2)$ and $\Delta_{T'}(I_1, I_2)$ in terms of $L(T,T')$. It means that finite transform set is more efficient than the complete one [7]. In the proposed algorithm, we apply the $\delta n_1$-cover affine transformations,

where $\delta \in (0,1]$ is used as an accuracy parameter for the algorithm input. A fast randomised method is provided inthe fast-match algorithm to obtain a transformation $T$ with high probability.

**Input:** Color images $I_1$,$I_2$ and a precision parameter $\delta$;
**Output:** A transformation $T$;
1: Create a net $N_{\delta/2}$ that is a $\delta_{n_1}/2$-cover of the set of affine transformations;
2: For each $T \in N_{\delta/2}$ approximate $\Delta_T(I_1, I_2)$ to within precision of $\delta/2$.Denote the resulting value $d_T$;
3: Return the transformation $T$ with the minimum value $d_T$.

**Fig. 7** *Algorithm 2: Approximating the best transformation*

**Input:** Color images $I_1$ and $I_2$, a precision parameter $l$ and a transformation $T$;
**Output:** An estimation of the distance $\Delta_T(I_1, I_2)$;
1: Sample $m = \Theta(1/l^2)$ [7] denotes values of pixels $p_1 \ldots p_m \in I_1$;
2: Return $\Delta_T(I_1, I_2) = \frac{1}{n_1^2} \sum_{p \in I_1} W(I_1(p), I_2(T(p)))$.

**Fig. 8** Algorithm 3: Transformation evaluation

*3.2 Regional colour constant:* Annual inspection labels $I_1$ and $I_2$ are extracted from the query vehicle and the dataset, respectively. At first, the logarithm of the colour values in $I_1$ and $I_2$ are calculated. Then their derivatives are obtained by the Laplace formula so as to produce a new three tuple. The mathematical description is as follows:

$$J_k(x, y) = \ln(I_k(x, y)), \qquad (7)$$

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where $J_k(x, y)$ is the logarithm, $k = 1,2,3$, and $I_k(x, y)$ represents the value of $R,G, B$ in $(x, y)$

$$D_{m,k}(x, y) = \nabla_m J_k(x, y), \quad (8)$$

where $D_{m,k}(x, y)$ is the derivative operator, $m = 1,2,3,4$ represents four directions.

## METHODSUSED IN COLOUR FAST-MATCH FOR PRECISE VEHICLERETRIEVAL

Our algorithm can be mainly divided into five steps. Firstly, we extracted the annual inspection labels from the target vehicle image. Secondly, the labels are used to approximate the best transformation evaluation and the transformation evaluation is calculated then. Thirdly, we calculated the regional colour constant. Fourthly, we extracted the H–S feature from the labels. Last but not least, the branch-and-bound method is applied for the target vehicle retrieval.

1.Preliminaries and the best transformation evaluation

2. Regional colour constant and the H–S colour histogram

3. Recognition and retrieval

4. Proposed retrieval algorithm

## RESULT

### 4.1 Datasets and experimental settings

The whole system is implemented on the Tensor flow platform. In our experiments, the vehicle ID vehicle dataset is applied. It contains vehicle images captured by multiple surveillance cameras in real scene. More importantly, the properties of each vehicle are almost annotated well, such as the bounding box, model, colour, and license plate number.

**Input:** Color vehicle image $I_1$ and $I_2$;
**Output:** The distance $d^2_{hist}$ between $I_1$ and $I_2$;
Extract special marks $i_1 \in I_1$ and $i_2 \in I_2$;
**for** $i_1 \in I_1$ **do**
Calculate score coefficient $\Delta G$ using Algorithm 1;
    **for** $i_2 \in I_2$ **do**
Calculate the SAD distance between $i_1$ and $i_2$ using Equation (3) and (5);
Approximate the Best Transformation Evaluation using Equation (6);
Return the transformation $T$ with the minimum value $d_T$ using Algorithm 2;
Calculate Transformation Evaluation $\Delta_T(i_1, i_2)$ using Algorithm 3;
    **end for**
Calculate Regional color constant $H(d_{m1}, d_{m2}, d_{m3})$ using Equation (7) and (8);
Extract H-S feature and Calculate the distance $d^2_{hist}$ using Equation (9);
Return the minimum $d^2_{hist}$ as the Euclidean distance between $I_1$ and $I_2$;
**end for**

**Fig. 10** Algorithm 4: The proposed retrieval algorithm

Each vehicle image in the dataset is assigned an ID based on its license plate number; a total of 237,393 images of 38,646 vehicles. For the reason that vehicle license plate is usually not a key feature in vehicle retrieval, the plates of all vehicles in the vehicle ID are covered by a mask. In our experiments,

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we use vehicle colour and model features as coarse grained attributes, with the colour divided into eight classes and the model divided into 250 classes.

**4.2 Comparative results**

***4.2.1 Vehicle detection**:* The vehicle detection is an important part of the vehicle retrieval application system. The detection of a complete and clear vehicle is very important for extracting colour information and vehicle inspection mark information. Meanwhile, the time efficiency of vehicle detection has a significant impact on the effectiveness of the whole vehicle retrieval system. There are two main reasons as follows: first, vehicle detection is the most important part of the time consumption through experimental observation; second, vehicle detection process requires a good hardware environment. In summary, vehicle detection plays an important role in the whole vehicle retrieval system. The purpose of vehicle detection is to solve the problem of vehicle and background classification in frame image of road surveillance video. With regard to this, the latest research shows that the most effective method for vehicle detection is deep learning framework. Therefore, the deep learning framework is applied in the proposed algorithm to improve the accuracy of vehicle retrieval.

***4.2.2 Vehicle fine-grained retrieval**:* We conducted a large number of experimental comparisons in terms of colour fast matching, regional colour constants, and H–S colour feature. In order to verify the performance of colour fast match, we experiment with many existing methods, including the original fast match, OpenCV-based template matching, and the matching method presented in [17]. Meanwhile, we conduct experiments in these two datasets and analyse the performance of the proposed algorithm for different qualities of images.

**Table 1** Vehicle retrieval accuracy of different match methods on VehicleID and ReIDcar

| Accuracy | OpenCV | Original fast-match [7] | Method by [17] | Our method |
|---|---|---|---|---|
| vehicle ID | 0.603 | 0.746 | 0.744 | **0.822** |
| reIDcar | 0.655 | 0.739 | 0.716 | **0.812** |
| average Time | 120 | 64 | 52 | **43** |

**Table 2** Comparison of our method with other six state-of-the-art methods on VehicleID and ReIDcar datasets in terms of vehicle retrieval accuracy

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| Accuracy | Deep hashing [15] | Method by [13] | DRDL [2] | Method by [33] | Method by [34] | Method by [21] | Our method |
|---|---|---|---|---|---|---|---|
| black | 0.745 | 0.779 | 0.781 | 0.623 | 0.687 | 0.765 | **0.796** |
| blue | 0.756 | 0.785 | **0.789** | 0.650 | 0.660 | 0.719 | 0.776 |
| cyan | 0.749 | 0.789 | 0.775 | 0.698 | 0.682 | 0.673 | **0.793** |
| green | 0.746 | 0.776 | 0.805 | 0.690 | 0.702 | 0.721 | **0.792** |
| grey | 0.751 | 0.783 | 0.802 | 0.702 | 0.680 | 0.766 | **0.812** |
| red | 0.754 | 0.789 | **0.796** | 0.671 | 0.704 | 0.677 | 0.787 |
| white | 0.741 | 0.787 | 0.778 | 0.682 | 0.659 | **0.799** | 0.794 |
| yellow | 0.753 | 0.790 | 0.789 | 0.686 | 0.632 | 0.707 | **0.798** |

***4.2.3 Vehicle retrieval algorithm comparison:***In order to evaluate our proposed method more comprehensively, other six state-of-the-art vehicle retrieval algorithms are carried out as comparative experiments. The comparison results are shown in Table 3.

The experimental results in Table 3 show that the DRDL framework achieves the best performance on the blue and red subsets, while the proposed method is best in the other five subsets [35, 36]. Although our method is far from perfect, it gets the first place in black, cyan, green, grey, and yellow datasets. We designed these experiments to measure how much improvement the full use of vehicle annual inspection labels in our framework brings.

### 4.3 Experimental analysis

In order to be more intuitively, Fig. 13 shows three query vehicle images and their retrieval results including the top three vehicles with the highest similarity. As can be seen, it is robust to interference factors, such as vehicle colour and vehicle type.

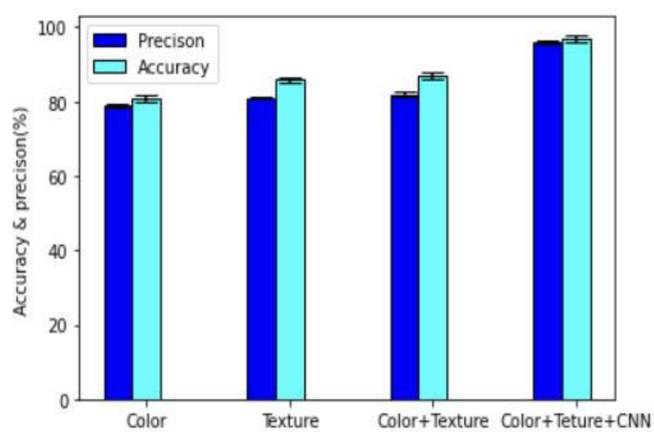


**Fig. 12** Ablation comparison of using four different fine-grained retrieval methods on eight colour vehicle subsets. Exp. 1 to 4 correspond to four methods, namely without region colour constant and H–S colour feature, with region colour constant, with H–

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S colour feature, and with both two features above

However, when faced with complex environmental conditions, our proposed vehicle retrieval system did not get the best performance. First of all, when vehicle pictures are too vague to identify vehicle annual inspection labels, our vehicle retrieval framework cannot extract the fine-grained features effectively.

**ADVANTAGES**

1. Precise vehicle retrieval
2. Feature matching method
3. Best transformation evaluation
4. High-quality and large-scale vehicle retrieval

**DISADVANTAGES**

The proposed algorithm has some limitations. First, for bad weather and poor monitoring equipment, the quality of the obtained vehicle image is not ideal. That is to say, the success rate of vehicle retrieval is lower in this case, which gives our work brings challenges and is the focus of future work. Second, due to the different traffic regulations between the regions, the vehicle annual inspection sign used in the vehicle retrieval are different, that is to say, the fine-grained features extracted are different, the proposed algorithm cannot be used to detect vehicles in all regions, which is only suitable for mainland China. The vehicle annual inspection sign is an important method of traffic control in China. The fine-grained features used in the proposed algorithm mainly depend on vehicle annual inspection sign.

**APPLICATIONS**

1. Intelligent traffic system
2. Accurate vehicle retrieval
3. Recognition and retrieval
4. Vehicle retrieval system

**CONCLUSION**

To solve the vehicle fine-grained retrieval problem, we present an improved fast affine matching method combining the regional colour constant and H–S colour feature of the vehicle annual inspection label for vehicle fine-grained retrieval. We perform effective and extensive experiments on two datasets with up to one million vehicles. Compared with several advanced current methods, the application of vehicle annual inspection labels contributes to the higher predict accuracy. Comprehensive experiments illustrate that the presented method outperforms other traditional methods. From the above, we believe that the proposed method can be widely implemented in a vehicle retrieval system.

**FUTURE SCOPE**

Compared with several advanced current methods, the application of vehicle annual inspection labels contributes to the higher predict accuracy. Comprehensive experiments illustrate that the presented method outperforms other traditional methods. From the above, we believe that the proposed method can be widely implemented in a vehicle retrieval system.

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