https://doi.org/10.2352/ISSN.2470-1173.2018.10.IMAWM-467

Vision based vehicle re-identification by fusion of multiple features

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Abstract

This paper presents a new vision based approach to vehicle re-identification (VRI) for smart transportation systems by fusion of multiple features. Unlike the conventional VRI systems which adopted loop sensors to capture inductive features for classification, we developed a hierarchical method for VRI by coarse-to-fine image matching. More specifically, VRI is performed at fine level by image matching using distinctive and anonymous features which are extracted from the large number of interesting points detected from the vehicle and its license plate images at coarse level. To achieve robustness, the thresholding of matching criteria is based on the dynamic analysis of the time series of vehicle images rather than predefined. In addition, the fusion of multiple features is conducted via a weighted probability scheme. To demonstrate the feasibility of the proposed new approach, a series of field testing were conducted, where 301 vehicles were considered for data calibration and 1699 vehicles were used for validation tests. The accuracy of matching rate reaches 73.51%. 85.52% and greater than 90% respectively by using density features, fusion of selected distinctive features and fusion of multimodal features.

Introduction

Vehicle re-identification (VRI) is concerned with matching vehicles between two points on a roadway. It plays an important role in smart transportation systems with various services such as travel time estimation, enforcement in free-flow ETC (Electronic Toll Collection) systems, detection of road accident and parking management, etc.

In previous studies sensor, feature, fusion method and outlier filtering were focused. Loop sensors were frequently used in many VRI systems such as [1~8]. In these loop-sensor based VRI systems, features including lengths, shapes, inductance waveform information, lane information, velocities and travel time information were analyzed and utilized. Other sensors, such as motion sensors providing vehicle axle information [9] and magnetic sensors providing magnetic waveform information [10], were also presented. Recently, vision-based sensors providing vehicle color information [11~13]. In addition to length and color, vehicle type information can be also be extracted for VRI in [14,15,16]. Nevertheless, vision information used in previous studies were raw features that limited the performance of VRI. Different criterions were introduced in [1,2,4,15] in order to fuse different features. Artificial intelligent methods were proposed by [5,8], while weighted arithmetic mean methods were utilized in [11~13]. Probabilistic based methods were raised from [9,10] and extended in [15]. Even though outliers can be filtered out by different criterions in [1,3,4], the travel time window method became popular in previous studies such as [2,9,15,16,17,18]. In a word, it is a trend to use vision sensor, travel time window and probabilistic fusion method to realize VRI system in previous studies.

Although there have been extensive studies on effective approaches to meet the increasing needs in real-world environment over the past decades, it remains a challenging task to develop robust classification algorithms which can handle various conditions such as noise, cluttered background, appearance variations due to illuminations, occlusions, viewpoints and complex object motion. Such algorithms are also expected to be adaptive and fast to achieve high performance. A vision based approach which adopts a new robust and adaptive detector based on the fusion of multiple features with learning capacity is regarded as effective to tackle the problems.

To overcome the limitations of the existing VRI systems which mainly rely on global raw features of vehicles (color, length and model type) and enhance the performance with multi-view and privacy protection, a vision-based approach for anonymous vehicle re-identification in a hierarchical manner is proposed. More specifically, three major tasks are focused in this paper: data collection, vehicle feature extraction and analysis, system calibration and validation.

System Framework

Video sequences will be processed to obtain vehicle images and license plate images. Vehicle alternatives will be collected according to a valid travel time window before extracting global and distinctive features. These features will be fused by a probabilistic method in order to solve the vehicle multiple to multiple matching problem. Finally, matched vehicles can be used for applications of intelligent transportation systems. The VRI system framework is depicted in Fig. 1.、

In previous studies [11,16,17], the linear weighted log-opinion pool method [19] was very popular in fusing probabilities of features distances. Besides, the VRI problem was actually a N to M matching problem in [11,16,17] which is rewritten in Equation (1) with a formulated problem presented as Equation (2) shown.

$$U(1,2,3,\cdots,i,\cdots,N) \rightarrow Q(1,2,3\cdots,j,\cdots,M,1,2,3,\cdots,\tau,\cdots,N) \quad (1)$$

$$u^* = \mathrm{argmax}\{P(D|u)P(u)\} = \boldsymbol{argmin}\{-\ln(P(D|u)) - \ln(P(u))\} \quad (2)$$

where U is the vehicle data set detected at the upstream station, Q is the vehicle data set selected at the downstream station, N is the number of vehicles detected at the upstream station, M is the number of vehicles selected at the downstream station, τ is a symbol of virtual vehicles, u^* is the optimum result of VRI problem, D is a vector of feature distances.

P(D|u) is the posterior probability and it is a weighted multiplications of probabilities, when *P(u)* is the prior probability and it is estimated from historical travel times.

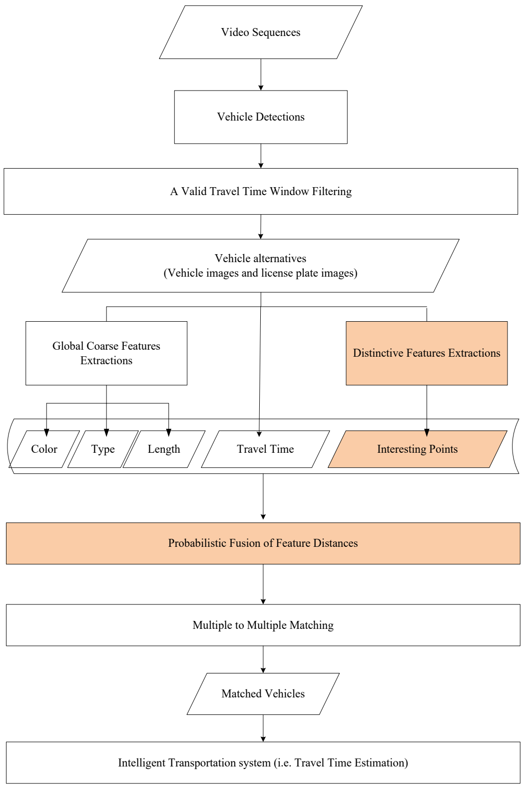


Fig.1 The VRI system framework

The VRI problem is an N to N+M matching problem. Let p_1 indicate the PDF of the same vehicle and let p_2 represent the PDF of different vehicles. Then, statistical analyses of feature distances can be implemented by using the calibration data set. PDFs of different feature distances are estimated by utilizing EM algorithm [20] based on the mixture Gaussion Model [21].

For each of possible matched vehicles, the probability of paired vehicle i and vehicle j can be calculated from Equation (3) and Equation (4) by applying the probabilistic fusion method according to Probability Theory.

$$\lambda(\mathrm{i},\mathrm{j}) = \rho^{\omega_1}(d_1)\rho^{\omega_2}(\mathrm{d}_2)\cdots\rho^{\omega_k}(\mathrm{d}_k)\cdots\rho^{\omega_K}(\mathrm{d}_K) \quad (3)$$

$$\lambda(\mathrm{i},\tau) = \xi^{\omega_1}(d_1)\xi^{\omega_2}(\mathrm{d}_2)\cdots\xi^{\omega_k}(\mathrm{d}_k)\cdots\xi^{\omega_K}(\mathrm{d}_K) \quad (4)$$

$$0 < \omega_k < 1 \ and \sum_{k=1}^{K}\omega_k = 1 \quad (5)$$

$$\rho(\mathrm{d}_k(i,j)) = p_1(\mathrm{d}_k(\mathrm{i},\mathrm{j}))\prod_{m=1,m!=j}^{M}\mathrm{p}_2(\mathrm{d}_k(\mathrm{i},\mathrm{m})) \quad (6)$$

$$\xi(\mathrm{d}_k(i,\tau)) = \prod_{j=1}^{M}\mathrm{p}_2(\mathrm{d}_k(\mathrm{i},\mathrm{j})) \quad (7)$$

$?(i,j)$ is a probability indicates vehicle i and j are the same vehicle with multiple features. $?(i,j)$ is a result of weighted multiplications of $?(d_k(i,j))$. $?(d_k(i,j))$ is a probability of vehicle i and vehicle j are the same vehicle with only a single feature $d_k(i,j)$. $\lambda(\mathrm{i},\tau)$ is a probability indicates there is no alternative vehicle for the vehicle i with multiple features. $?(i,j)$ is equal to the weighted multiplication of $?(d_k(i,j))$. $?(d_k(i,j))$ is a probability of the vehicle j is matched to a virtual vehicle with a single feature $d_k(i,j)$ even though there is a group of alternative vehicles. p_1 and p_2 is the probability of the same vehicle and different vehicles respectively with a single feature distance.

The calculation of $P(D|u)$ in Equation (2) can be illustrated as Equation (8)

$$\mathrm{P}(\mathrm{D}|\mathrm{u}) = \prod_{i=1}^{N}\prod_{j=1}^{M}\lambda(\mathrm{i},\mathrm{j})^{\delta(\mathrm{u}(\mathrm{i})=\mathrm{j})}\cdot\prod_{i=1}^{N}\prod_{j=1}^{M}\lambda(\mathrm{i},\tau)^{\delta(\mathrm{u}(\mathrm{i})=\tau)} \quad (8)$$

where $?(u(i) = j)$ and $\delta(\mathrm{u}(\mathrm{i}) = \tau)$ are impulse functions. A result of possible correct matching of i and j is indicated by $?(u(i) = j)$, while a possible virtual matching of i and τ is indicated by $\delta(\mathrm{u}(\mathrm{i}) = \tau)$. Duplicated matching is not allowed in the problem. Therefore, the N to M matching probability $P(D|u)$ is a result of multiplied probabilities of a group of unique matched vehicles.

By a series of evolvements, $lnP(D|u)$ becomes a formulation in Equation (9).

$$\mathrm{lnP}(\boldsymbol{D}|\mathrm{u}) = \sum_{k=1}^{K}\omega_k\left\{\sum_{i=1}^{N}\sum_{j=1}^{M}\delta(\mathrm{u}(\mathrm{i}) = \mathrm{j})\ln\left(\rho(\mathrm{d}_k(\mathrm{i},\mathrm{j}))\right) + \sum_{i=1}^{N}\sum_{j=1}^{M}\delta(\mathrm{u}(\mathrm{i}) = \tau)\ln\left(\xi(\mathrm{d}_k(\mathrm{i},\mathrm{j}))\right)\right\}$$

According to [16], $lnP(u)$ can be expressed as Equation (10).

$$\mathrm{lnP}(\boldsymbol{u}) = \boldsymbol{\alpha}\sum_{i=1}^{N}\sum_{j=1}^{M}\left\{\begin{array}{l}\ln(1-\theta)\dfrac{f(T(\mathrm{i},\mathrm{j}))}{\eta}\delta(\mathrm{u}(\mathrm{i}) = \mathrm{j})\\ +\ln(\theta)\delta(\mathrm{u}(\mathrm{i}) = \tau)\end{array}\right\} \quad (10)$$

$$\eta = \sum_{i=1}^{N}\sum_{j=1}^{M}[\![f(T(\mathrm{i},\mathrm{j}))]\!]\delta(\mathrm{u}(\mathrm{i}) = \mathrm{j}) \quad (11)$$

where $T(i,j)$ is the travel time of one possible vehicle matching result, while $f(*)$ is the travel time probability. θ is a travel time parameter and $0 \le \theta \le 1$. There is a little difference from [16] in this paper. α is introduced to analyze the influence of $lnP(u)$ in the VRI system and $\alpha = 1$ or α =0. If α =0, there is no contribution of travel time probabilities in the VRI system, and vice versa.

The multiple to multiple matching problem can be solved by the shortest path algorithm [22]. Nevertheless, an important job in the VRI system is to find out fusion weights of multiple features. Fusion weights can be obtained by utilizing the least square method [23] based on the calibration data. However, there is an easier way to generate fusion weights. *MEs* of *PDFs* can be used to get fusion weights by Equation (12).

$$\mathrm{w}_\mathrm{i} = {1-\mathrm{ME}_\mathrm{i}}\Big/{\sum_{i=1}^{N}(\mathrm{ME}_\mathrm{i})} \quad (12)$$

where w_i is the fusion weight of the i_{th} feature. ME_i indicates the ability of errorless matching in the VRI system using the i_{th} feature.

Data Collection

Data was collected from a gantry station at Lianhuachi north road in Beijing. There are four lanes on the road with the speed limitation of 80km/h. There were six HKVISION vision based sensors installed on the gantry and four of those were used to capture vehicles in front view and two of those were used to catch vehicles in rear view. Parameters of these sensors were shown in Table 1. The image resolution is 2048*1536, the camera type is 1/1.8’’ CCD, the frame rate is 25fps and each image size is about 400KB.

As Fig. 2 depicts, the y-axis is the projection line of the gantry, while the negative side of the x-axis is the travel direction. The front view detection region was about 13m to 20m, while the rear view detection region was about -13m to -20m on the travel direction. If considering the vehicle travel direction, vehicles in front view were upstream vehicles and vehicles in the rear view were downstream vehicles.

These upstream vehicle images were re-identified to their corresponding downstream vehicle images in this paper. Vehicle images, license plate images and recognized license plate numbers could be provided directly from installed vision-based sensors, which were embed image processing and recognition algorithms. Therefore, feature extraction, feature analysis and VRI can be focused in this paper.

Table 1. The specification of vision-based sensors

Parameter	Value
Installation angle	about 35 degree
Front View Detection Region	about 13m to 20m
Rear View Detection Region	about -13m to -20m
Image Resolution	2048*1536
Camera Type	1/1.8’’ CCD
Frame Rate	25 fps
Image Storage Size	about 400 KB

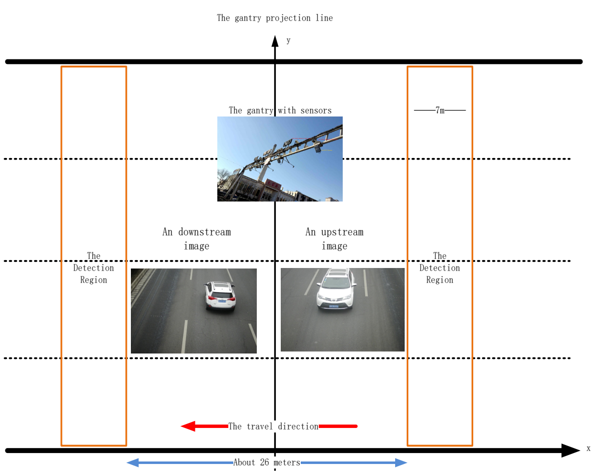


Fig.2 Vehicle detection on the data collection site

Fig. 3 is a snapshot of the software interface of the data collection system. 2000 paired vehicle images, including their front view, rear view images and license plate images were collected on this data collection site for the software. These images were divided into two sets. One was the calibration set. Another was the validation set. There were 301 vehicle images and license plate images in the calibration set, while 1699 vehicle images and license plate images were included in the validation set.

Fig.3 The snapshot of data collection software

These 301 vehicles was collected in the period of 13:09 to 20:34 on 18th, April, 2016. Other 1699 vehicles was collected in the period of 13:09 to 20:34 on 18th, April, 2016. In addition, recognized license plate numbers were used as ground truths.

Feature Extraction and Analysis

Vehicle detection is not focused in this paper and its results were provided by vision-based sensors. However, vehicles can be detected accurately by currently hot deep learning methods such as the SSD method [24].

Similar to [16], raw features such as color, type and length were extracted from vehicle images. In addition, distinctive features of vehicle images and license plate images were calculated. In order to correspondence with [16], the Bhattacharyya distance of HSV color histograms, the summation of absolute differences of template matching results and the normalized absolute difference of length were calculated between vehicle images. Nevertheless, there was an important difference in this paper: distinctive features were utilized. Distinctive features were interesting points such as corners, blobs and T-junctions that detected by the SURF algorithm [25]. These detected interesting points are robust for complex conditions such as changed weather and varied illuminations. In this paper, the Hessian threshold is 400, the number of octaves is 3 and the number of octave layers is 4 in the SURF algorithm.

Interesting points from two images can be matched using the k-Nearest Neighbors algorithm [26], where k is set to one in this case. The distance of matched interesting points can be calculated from Equation (13).

$$d_{ip}(i,j,k) = V_i(k) - V_j(k) \qquad (13)$$

where V is a 64-dimension feature vector of an interesting point, k is the index of matched interesting points between images, i and j are indexes of images in front view and in rear view respectively.

Therefore, various distinctive feature distances between images can be extracted. These distinctive feature distances can be defined as following,

ADI(i,j), the average distance of matched interesting points between two images,

VDI(i,j), the variance of distances of matched interesting points between two images,

NI(i,j), the number of matched interesting points between two images,

ADIT(i,j), the average distance of matched interesting points between two images only if $d_{ip}(i,j,k)<0.25$,

VDIT(i,j), the variance of distances of matched interesting points between two images only if $d_{ip}(i,j,k)<0.25$, NIT(i,j), the number of interesting points between two images only if $d_{ip}\ (i,j,k)<0.25$.

Particularly, *ADI* can be calculated as Equation (14) and *VDI* can be obtained by Equation (15). Both *ADI* and *VDI* are mean square distances.

$$\mathrm{ADI}(i,j)=\sqrt{\frac{1}{K}\sum_{k=1}^{K}d_{ip}^{2}(i,j,k)} \tag{14}$$

$$\mathrm{VDI}(i,j)=\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left[d_{ip}(i,j,k)-\mathrm{ADI}(i,j)\right]^{2}} \tag{15}$$

where $K=64$ is the number of components in V. Above-mentioned distinctive feature distances are calculated not only from vehicle images but also license plate images. Color, type, length and distinctive features are anonymous features so that privacy problem can be ignored. By introducing distinctive features, the performance of the VRI system can be improved, which can be shown in experiment results.

Fig. 4 is an example of matching multiple vehicle images using color distances. Intuitively, color histograms that are looked alike should belong to the same vehicle. Similar behaviors could be found in type and length features.

However, it is difficult to distinguish vehicles with similar color, type and length. Distinctive features would be very useful for discriminating these similar vehicles. As Fig. 5 depicts, there were many interesting points can be matched by vehicle images from the same vehicle, while only a few for different vehicles.

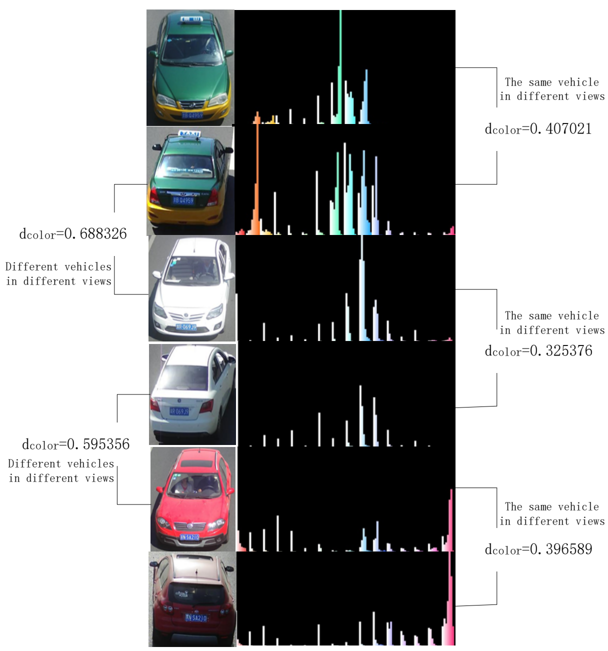
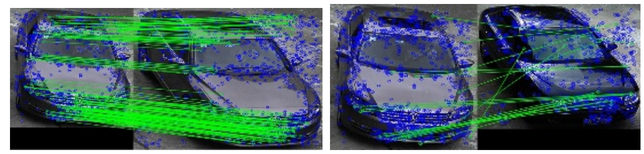


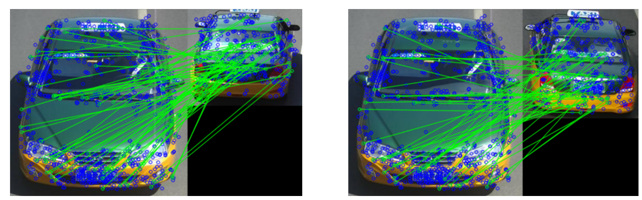
Fig.4 Examples of color distances



(a) (b)

Fig.5 (a) the same vehicle (b) different vehicles

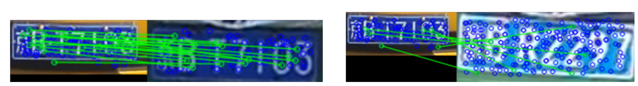
Examples in Fig. 5 are vehicle images all in the front view. For vehicle images in different views, the situation is going to be worse. Particularly, in this paper, vehicle images in the front view will be matched to vehicle images in the rear view. Only partially overlapped information remained in both front view and rear view images. Fig. 6 shows examples of vehicle image interesting point matching in opposite views. Visually, it is hard to distinguish two similar green taxies (one is *710*, another is *R22*) even though the interesting point matching is applied. In order to analyze the subtle difference between vehicle images, all of distinctive features including *ADI*, *VDI*, *NI*, *ADIT*, *VDIT* and *NIT* should be calculated and further checked.



(a) (b)

*Fig.6 Matching of green taxies images (a) *710* to *710* (b) *710* to *R22**

Furthermore, it can be found that interesting points from license plate images are notable for VRI. Many similar interesting points can be found in license plate images from the same vehicles even they were captured in opposite views, as Fig. 7 depicts.



(a) (b)

*Fig.7 Matching of license plate images (a) *710* to *710* (b) *710* to *R22**

In order to better use vehicle features, probabilities of feature distances are utilized in the VRI system. Therefore, different features in different dimensions and units can be integrated easily. Besides, one better way to represent similarities between vehicles is to utilize probabilities of their feature distances which was presented in many previous studies.

Examples of *PDFs* of *DT*, *ADI-V* (*vehicle image*), *NI-V* (*vehicle image*) and *ADIT-LP* (*license plate image*) are displayed in Fig. 8. Misclassification errors (*ME*) can be calculated from the estimated *PDFs*. *MEs* of *PDFs* of global raw features and some of those from *PDFs* of distinctive features are listed in Table 2.

Except for global raw features (*DC*, *DT* and *DL*), other *MEs* from distinctive features are larger than 60% which are not shown in the table. It can be found that distinctive features listed in Table 2 have much less *MEs* than global raw features. These distinctive features should be better than global features.

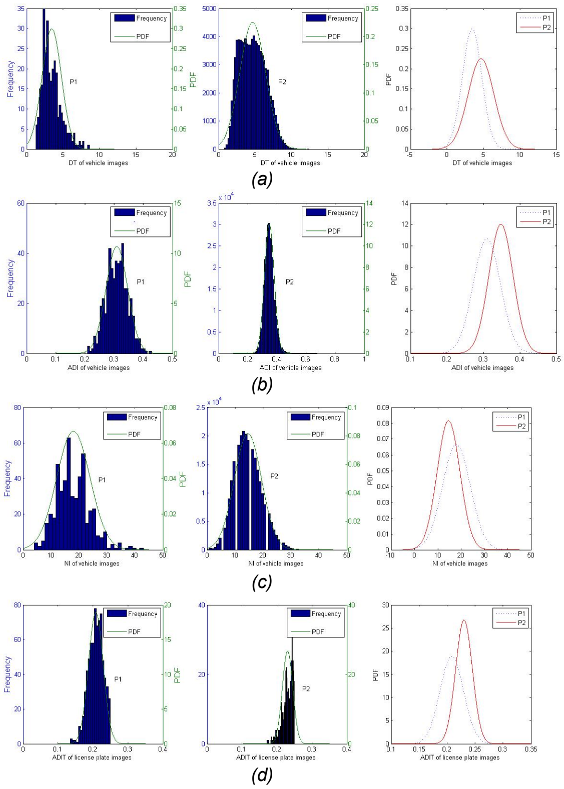


Fig.8 PDFs of different features (a)DT (b)ADI-V (c)NI-V (d)ADIT-LP

Therefore, *ADI-V*, *NIT-V*, *NI-LP*, *ADIT-LP* and *NIT-LP* are selected for the VRI system with *DC*, *DT* and *DL*.

Table 2. The specification of vision-based sensors

Features	*The misclassification error (ME)*
DC	*82%*
DT	*67.28%*
DL	*95.41%*
ADI-V	*58.14%*
NIT-V	*41.36%*
NI-LP	*52.21%*
ADIT-LP	*52.97%*
NIT-LP	*32.36%*

System Calibration and Validation

The problem of Equation (1) and Equation (2) was formulated as a minimum cost and maximum matching problem [16] which was solved by the shortest path algorithm [22]. Before solving the above-mentioned problem, *P(u)* and the travel time window should be obtained first. In this paper, the *PDF* of historical travel time is used for deciding *P(u)* and the travel time window. Historical travel time is acquired from the calibration data set. The PDF of historical travel time is shown in Fig. 9 with mean u = 1737.9ms and standard deviation σ=767.2ms. Thus, by considering 95% confidence level, the travel time window should be [203.5ms, 3272.3ms].

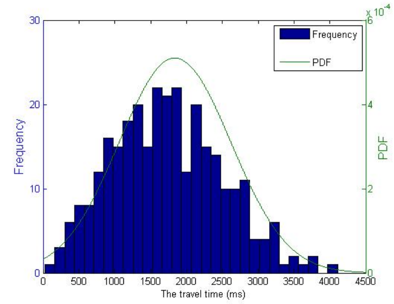


Fig.9 The histogram and the PDF of travel times of the calibration data

In this paper, even though there are many distinctive features, global features (*DC*, *DT* and *DL*) and some of distinctive features (*ADI-V*, *NIT-V*, *NI-LP*, *NIT-LP* and *ADIT-LP*) are used in the proposed VRI system in order to present the result quickly. Fusion weights are calculated from *MEs* of these features based on the proposed ME criterion and the calibration data set.

The validation data set includes 1699 vehicles which were both detected in the front view and in the rear view. These vehicles are re-identified in the proposed VRI system on each 1min interval with the valid travel time window [203.5ms, 3272.3ms].

Re-identification results of the proposed VRI system without and with distinctive features are shown in Table 3 and Table 4 respectively. Parameters of the VRI system are also presented in these tables. In Table 3, only *DC*, *DT* and *DL* are used. In Table 4, *ADI-V*, *NIT-V*, *NI-LP*, *ADIT-LP* and *NIT-LP* are introduced with *DC*, *DT* and *DL*. *P(u)* is not used (α=0) in order to find out the influence of distinctive features. It can be found that the correct matching rate (*CMR*) can be raised from 31.90% to 57.62% by introducing distinctive features. If *P(u)* is used (α=1), the result will be better, i.e. 31.90% to 73.51% and 57.62% to 85.52%. In this paper, wrong matching rate (*WMR*) and virtual matching rate (*VMR*) are also calculated.

Table 3. Re-identification results of the basic VRI system without distinctive features

	α	θ	*CMR*	*WMR*	*VMR*
$?_{DC} = 0.3254$					
$?_{DT} = 0.5916$	*0*	*-*	*31.90%*	*37.02%*	*31.08%*
$?_{DL} = 0.0830$	*1*	*0.4*	*73.51%*	*3.12%*	*23.37%*

Table 4. Re-identification results of the basic VRI system with distinctive features

	α	θ	*CMR*	*WMR*	*VMR*
$\omega_{DC} = 0.0566$, $\omega_{DT} = 0.1028$, $\omega_{DL} = 0.01442$, $\omega_{ADI}-V = 0.1315$, $\omega_{NIT}-V = 0.1842$, $\omega_{NI-LP} = 0.1502$, $\omega_{ADIT}-LP = 0.1478$, $\omega_{NIT-LP} = 0.2125$	*0*	*-*	*57.62%*	*25.19%*	*17.18%*
	1	*0.4*	*85.52%*	*2.24%*	*12.24%*

In order to better present the performance of proposed VRI system, different combinations of features were analyzed. In this paper, for combinations without travel time probabilities, α=0. For the combination with travel time probabilities, α=1 and θ=0.2. The travel time window is [203.50ms, 3272.30ms]. Besides, fusion weights of feature distances are decided by the ME criterion.

There are six types of combinations,

(i) *GF* only, only global features are used.

(ii) *GF* and *DF-LP*, global features and distinctive features of license plate images are used.

(iii) *GF* and *DF-V*, global features and distinctive features of vehicle images are used.

(iv) *GF*, selected *DF-V* and selected *DF-LP*, global features, selected distinctive features of vehicle images and selected distinctive features of license plate images are used.

(v) *GF* and *DF-V* and *DF-LP*, global features, all distinctive features of vehicle images and license plate images are used.

(vi) *GF* and *DF-V* and *DF-LP* and time, global features, all distinctive features of vehicle images and license plate images, and time probabilities are used.

From Table 5, it can be found that by introducing more features especially distinctive features, the *CMR* will be better. The best *CMR* 92.58% is obtained by fusing all global features, all distinctive features and travel time information.

Table 5. Performances of different feature combinations in the VRI system

Features	*CMR*	*WMR*	*VMR*
GF only	*31.90%*	*37.02%*	*31.08%*
GF and DF-LP	*31.84%*	*61.57%*	*6.59%*
GF and DF-V	*46.62%*	*7.65%*	*45.73%*
GF, selected DF-V and selected DF-LP	*57.62%*	*25.19%*	*17.19%*
GF, DF-V and DF-LP	*60.21%*	*21.84%*	*17.95%*
GF, DF-V, DF-LP and time	*92.58%*	*3.53%*	*3.88%*

Conclusion and Future Work

In this paper, distinctive features were introduced into the VRI system. The software interface of a demonstration of the VRI system is presented in Fig. 10. In this system, multiple features including global, distinctive and time features can be selected for VRI according to computation requirements and real situations.

These distinctive features were extracted from vehicle images and license plate images. Vehicles with similar global features (color, type and length) can be separated well by using distinctive features. Even though distinctive features of license plate images were used, license plate numbers cannot be re-constructed from these anonymous features. Fusion weights of multiple features can be generated by the ME criterion which is an easier way than the least square method or exhaustion methods in previous studies.

The accuracy of the VRI system can be enhanced significantly with distinctive features. The *CMR* is 31.90% if only using global features and it is 57.62% if selected distinctive features are used. In addition, the *CMR* is up to 60.21% when all distinctive features are utilized. After introducing travel time information with an optimum calibrated parameter, the *CMR* can be increased to 92.58%. Furthermore, vehicles were first re-identified in different views in this paper which was another key extension of previous studies. Particularly, vehicle images in front view were matched to their corresponding images in rear view in this paper.

In the future, deep features generated by deep learning methods will be very useful for the VRI system. Fusion weights should be dynamic and decided by characteristics of features extracted in each round of matching. If possible, the multiple to multiple matching network in the VRI system can be evolved into a supervised training framework where fusion weights can be updated automatically.

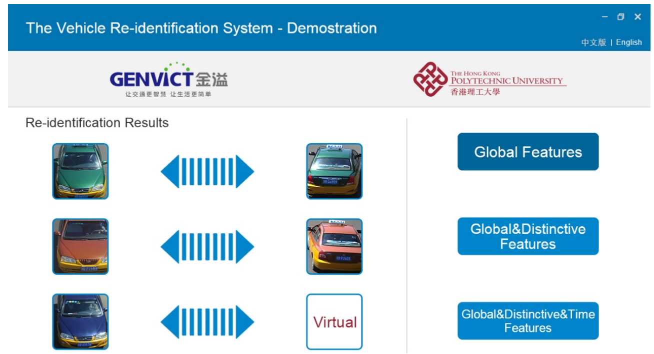


Fig.10 A demonstration of the VRI system

Acknowledgement

The authors would like to thank the support from Shenzhen Genvict Technologies Co. Ltd, The Hong Kong Polytechnic University and Zhujiang Scholar Scheme with Shenzhen Institute of Information Technology.

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