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Vehicle Re-Identification Using Deep Learning Methods with a Focus on Challenges and Recent Solutions

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Abstract: Vehicle re-identification (Re-ID) is essential in intelligent transportation systems and surveillance, facilitating vehicle tracking and monitoring across diverse scenarios. In recent years, vehicle Re-ID has seen significant progress, primarily driven by advancements in deep learning. Therefore, this article aims to help researchers grasp the latest developments and identify future trends in the field. First, we explore the state-of-the-art deep learning techniques that have significantly enhanced the accuracy and efficiency of vehicle Re-ID, which have shown exceptional prowess in extracting and learning discriminative features from vehicle images. Additionally, we present a multidimensional classification that classifies existing deep learning-based vehicle re-identification methods into three groups: metric learning approaches, part-based approaches, and generative adversarial learning approaches. Finally, we address some challenges and suggest potential research directions for vehicle Re-ID. Through this paper, we aim to provide a nuanced understanding of the current landscape of deep-learning techniques in vehicle Re-ID, offering insights into their capabilities and limitations and paving the way for future research in this vital area.

Keywords: *Machine Learning, Deep Learning, Computer vision, intelligent transportation system, Vehicle Re-identification*

1. Introduction

In the past few years, vehicle re-identification (Re-ID) has received considerable attention owing to its significant role in a large number of systems and applications such as parking management systems, intelligent traffic-management systems, and surveillance systems where monitoring and tracking vehicles are essential for security, safety, and efficiency [4]. Vehicle Re-ID aims to retrieve the same vehicle from multiple cameras with variant viewpoints, lighting conditions, pose changes, and partial occlusion [6]. These surveillance camera networks are spread in several broad geographical areas on main or Sub-roads with non-overlapping coverage and generate many surveillance videos daily. These videos analyze vehicle paths to control traffic and follow up on violators of traffic and guidance laws and regulations. The adoption of convolutional neural networks (CNNs)[7, 10], in particular, has played a transformative role in feature extraction and representation learning, providing the backbone for many state-of-the-art vehicle Re-ID frameworks[7, 11, 12]. However, despite remarkable progress, the field continues to grapple with several challenges, including but not limited to the scalability of Re-ID systems, generalization across diverse datasets, and the integration of temporal and spatial information.

This paper aims to summarize the advancements in vehicle Re-ID based on deep-learning techniques. In doing so, it provides a comprehensive overview of the methodologies that have been developed, the datasets and benchmarks that have been established, and the metrics that are commonly employed to evaluate performance. Moreover, it underscores the existing challenges that impede progress and identifies the gaps in current research. By synthesizing the latest knowledge and outlining open problems, this paper aims to foster further innovation in vehicle Re-ID and catalyze the development of more robust, efficient, and accurate systems. Through this examination, we intend to elucidate the intricate interplay between deep-learning algorithms and vehicle Re-ID tasks, providing a valuable resource for researchers and practitioners in computer vision and intelligent transportation systems.

The rest of this paper is structured in the following sections: In sec. 2, we review the past and recent deep learning-based approaches for vehicle Re-ID. In sec. 3, we discuss the standard datasets and evaluation metrics for vehicle Re-ID. In sec. 4, we compare the performance of various methods. In sec. 5, We present vehicle Re-ID challenges and recent achievements. Sec. 6, the conclusion.

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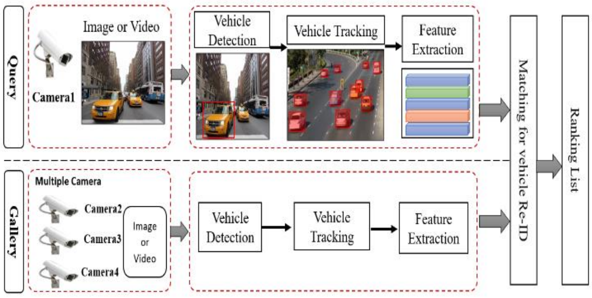

Fig.1 The comprehensive flow of the vehicle Re-ID system

2. Vehicle Re-ID Methods

Figure 1 illustrates the comprehensive flow of the vehicle Re-ID system, primarily comprising two distinct steps: The first step is vehicle detection, and the second step is Re-ID. For the initial step, vehicles are identified within each camera's frame, and each camera or sensor in a surveillance or monitoring system detects and localizes vehicles in its field of view using object detection algorithms. In recent years, numerous algorithms with exceptional vehicle detection accuracy have surfaced, such as single-shot-detector (SSD) [16], Fast R-CNN [17], YOLO, or You Only Look-Once [16]. The main task in re-identifying vehicles is to know the distinguishing features of vehicles to distinguish between images of vehicles with the same identity and those with different identities.

In this section, we highlight the methods used in vehicle Re-ID tasks in the past and present, given the rapid development of deep learning and machine learning.

2.1. Traditional Vehicle Re-ID Methods

Before the prevalent use of deep learning, traditional methods for vehicle Re-ID were based on extracting handcrafted features and using distance metrics for matching. Here, we outline some of these conventional methods.

2.1.1. Feature-Based Vehicle Re-ID Methods

Feature-based Vehicle Re-ID methods extract specific, distinguishable, and representative features from vehicle images, such as color, texture, shape, etc., which can effectively match and re-identify vehicles across non-overlapping camera views.

In the past, surveillance systems predominantly depended on manual monitoring and human operators, with minimal automation in vehicle tracking and Re-ID. R.T. et al. [19] developed a video surveillance and monitoring (VSAM) system. VSAM systems include a network of video cameras strategically placed to capture video footage in various areas or locations; the cameras record video footage continuously or in response to specific events or triggers. The recorded video data is often stored on digital or network video recorders. In [21], an edge-based model for vehicle Re-ID is proposed. Based on non-metric distance, the challenge of selecting models from two sets of identical vehicles is overcome in this model.

The Vehicle Re-ID task is divided into two parts: feature-learning and metric-learning. The Feature-learning task focuses on learning discriminative features of the vehicle to discriminate between images of vehicles with the same identity and specifications and those with a different identity. In contrast, the metric-learning task focuses on measuring the similarity between images of vehicles. A robust feature learning algorithm can overcome the obstacles of camera angle changes, pose changes, background interference, illumination changes, occlusion, and inaccurate target detection in different cameras. Also, using a robust metric learning algorithm, it is possible to make the space between images of the same vehicle smaller and the space between images of different vehicles larger. For that reason, a robust feature-learning algorithm and metric-learning algorithm are the key points for vehicle Re-ID.

While these methods were quite prevalent in the past, with the rise of deep learning, many state-of-the-art vehicle Re-ID methods now employ CNNs to automatically extract and learn robust features. Nevertheless, understanding feature-based methods is crucial as they lay the foundation for many modern techniques and can be integrated into hybrid approaches.

2.1.2. License Plate Recognition-Based Vehicle Re-ID Methods

Automatic License Plate Recognition (ALPR) systems started gaining popularity in the last decade. These systems focused on recognizing vehicle license plates, a critical step in vehicle Re-ID [24]. It involves using cameras and image processing techniques to identify and record license plates in real-time [27]. An ALPR system comprises two components: the initial license plate detection stage and the subsequent interpretation of the vehicle license plate image into a numerically readable format [29]. In the past two decades, numerous methodologies have been proposed for ALPR [30-32]. However, there are still difficulties in accurately detecting vehicles in images, as shown in Figure 2. Firstly, capturing vehicle images may not be executed flawlessly, resulting in potential imperfections. Additionally, certain characters within the images may be partially obscured, further complicating the detection process. Furthermore, the phenomenon of illumination and the subsequent reflection of headlights on license plates (LPs), as well as discrepancies in image sizes, different plate positions, camera distances, and zooming, contribute to the overall difficulty of this task [34].

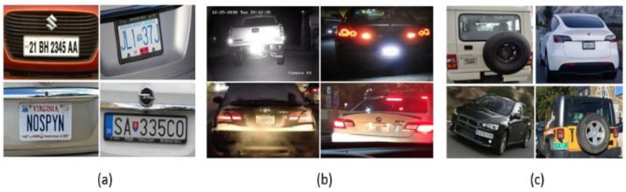

Fig.2 Some challenges in the LPR task. (a) License plates with different sizes, (b) The phenomenon of illumination and the subsequent reflection of headlights on license plates, (c) Different plate positions.

2.2. Deep learning-based Vehicle Re-ID

Deep learning, particularly CNNs, has revolutionized vehicle re-ID due to its ability to automatically learn discriminative features from large datasets. Deep learning-based methods generally outperform traditional feature-based methods by a significant margin. This section overviews deep learning-based vehicle re-ID approaches, as shown in Figure 3.

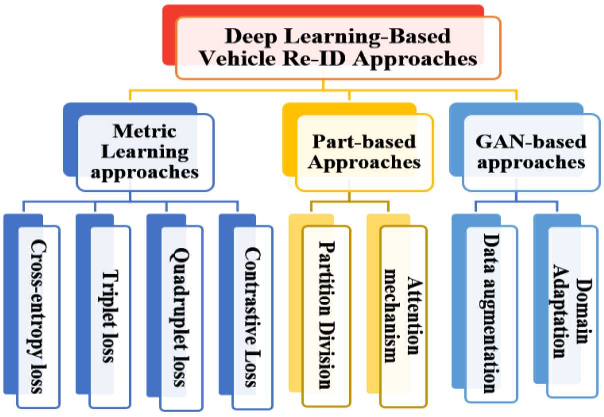

Fig.3 Structural organization of vehicle Re-ID methods based on deep learning

2.2.1. Metric Learning Approaches

Deep metric learning (DML) extends traditional metric learning by leveraging the representational power of deep neural networks to learn feature embeddings that can effectively measure similarities or distances between input data points. The goal is to discover a feature space where similar samples are close together while dissimilar samples are far apart [37]. DML has been successfully applied in various fields, such as Re-ID, Face verification and recognition, fine-grained classification, and face verification and recognition.

DML plays a significant role in achieving state-of-the-art results for vehicle Re-ID. The goal is to ensure that the feature embeddings of the same vehicle are close in the embedded space while those of different vehicles are farther apart. DML loss functions specify the target that the model optimizes for during training. They guide the model in learning a feature space where distances between embeddings reflect the similarities or dissimilarities of the original data points. Standard DML loss functions used in vehicle Re-ID tasks are cross-entropy loss [22, 38], contrastive loss [39, 40], triplet loss [41, 42], Center Loss, and Quadruplet Loss [43].

Cross-entropy loss: Cross-entropy loss is a widely used loss function in classification problems, and it can be effectively applied to vehicle Re-ID tasks, especially when treated as a multi-class classification problem [44]. In vehicle Re-ID, each vehicle identity (i.e., each unique vehicle) can be considered a separate class.

Triplet loss*:* The triplet loss function is a highly effective technique employed in deep learning for tasks such as vehicle Re-ID. Its objective is to acquire an embedding space wherein the distances between points accurately reflect the similarity of the samples. Specifically, in the domain of vehicle Re-ID, this implies that images depicting the same vehicle should be positioned nearby within the embedding space. In contrast, images representing distinct vehicles should be positioned further apart.

To enhance the efficacy of models, certain vehicle Re-ID methods based on deep learning employ a fusion of triplet loss and another loss function, such as Minyue Jiang et al. [45] used a combination of triplet loss and cross-entropy loss to improve their model. Combining these two losses in experiments has enhanced the model's ability to acquire discriminative features. In [46], The triplet loss is combined with the classification loss to improve the fusion network for vehicle Re-ID.

Quadruplet loss: Quadruplet loss function is a type of loss function used in deep learning, specifically for vehicle Re-ID. It is an extension of the triplet loss designed to ensure that an anchor image (a reference image) is closer to positive samples (images of the same vehicle) than to negative samples (images of different vehicles) by a margin. The quadruplet loss adds a negative sample to the triplet loss, resulting in four images: an anchor, a positive sample, a negative sample, and an additional negative sample.

2.2.2. Part-based Approaches

The Part-based method divides the vehicle image into different regions or parts, extracting individual features from each part. The idea is that more discriminative features can be captured by focusing on distinctive regions. It's somewhat analogous to human perception; when we try to recognize a vehicle, we might focus on specific parts like the front grille, headlights, license plate, and wheels, among others. In the last decade, representation-learning [47-49] methods focused on global deep discriminative features from vehicle images. On the other hand, the system is susceptible to various challenges, including alterations in pose, changes in perspective, and incomplete frames of vehicle detection, all of which directly impact retrieval accuracy. In the past, most high-performance vehicle Re-ID

[50, 51] methods usually used the technique of extracting part features and combining global features of the vehicle to obtain vehicle recognition information to overcome various retrieval challenges across cameras.

Several deep learning models integrate the part-based approach. For instance, models might employ multi-branch networks where each branch processes a specific vehicle region. Some works combine the part-based approach with attention mechanisms to dynamically focus on informative parts.

***Partition Division**:* Partition division in vehicle Re-ID refers to partitioning a vehicle image into separate regions or segments, facilitating the extraction of features from these regions individually. The goal is to capture fine-grained details and improve the discriminative power of the representation, especially in the presence of variations such as viewpoint changes, lighting conditions, and occlusions. Partition division methods play a crucial role in enhancing the effectiveness of vehicles. The division approaches can be summarized into two types, namely, uniform spatial-division approaches [4, 52] and part-detection approaches [17, 53]. Uniform spatial partitioning approaches are susceptible to partitioning imbalances and do not require partial annotation. Contrarily, the part detection approaches can mitigate misalignment but face high costs from additional manual part annotations and massive training computations [25].

***Attention mechanism**:* The attention mechanism methods play a crucial role in enhancing the accuracy and efficiency of vehicle instance retrieval in vehicle Re-ID. This mechanism is central to methods like the part-guided attention network (PGAN) [17], which recognizes fine-grained visual differences between vehicles by capturing global appearance and local part information. Tang et al. [54] proposed a PA-Net (Part-Attention Network) architecture network for vehicle Re-ID. PA-Net is introduced to identify various vehicle components attentively, which is easy to improve. These approaches tend to be more efficient than those relying on external tools, although they still face challenges such as background clutter and can be complex to train.

2.2.3. GAN-based approaches

Generative Adversarial Networks (GANs) [55] have gained popularity in various computer vision tasks, including vehicle Re-ID. GANs can generate new data samples that are indistinguishable from accurate data, and they can also be used to augment datasets, improve feature representation, and enhance domain adaptation. Here, we review how GANs can be applied to vehicle Re-ID.

Data augmentation： GANs can generate synthetic images of vehicles with different orientations, lighting conditions, and backgrounds. This helps increase the training set's diversity, which is crucial for improving the robustness of vehicle Re-ID models. Examples of GAN architectures that might be used for these purposes include Cycle-GAN [56] for style transfer and domain adaptation), Star-GAN [57] is used for multi-domain translation, and conditional GANs (cGANs) are used where the condition could be vehicle type or other attributes.

In [58], a novel data synthesis method for vehicle Re-ID has been proposed that focuses on local-region perspective transformation, combined with transformation state adversarial learning and a candidate pool. Compared to other methods, this approach is straightforward and effective, enhancing Re-ID accuracy by providing diverse training data. Zhang et al. [59] proposed a multi-view GAN (MV-GAN) that can collect actual vehicle images conditional on random structural views for vehicle Re-ID, particularly for viewpoint normalization.

These GAN-based data augmentation approaches are critical in enhancing vehicle Re-ID by addressing key challenges such as viewpoint variation, similarity among vehicle models, and the need for diverse training datasets. As the field progresses, these methods are likely to become even more sophisticated, contributing significantly to the accuracy and reliability of vehicle Re-ID systems in various applications.

Domain Adaptation： The domain adaptation problem in vehicle Re-ID arises when a model trained in one domain or dataset performs poorly when applied to a different domain. This issue is particularly relevant in vehicle Re-ID due to the variability in camera setups, environmental conditions, and vehicle types across various locations or datasets [60, 61]. Hence, numerous studies [62-64] in the past few years have focused on addressing domain adaptation challenges in cross-domain vehicle Re-ID tasks using GAN techniques.

Peng et al. [65] introduced the vehicle transfer generative adversarial network (VT-GAN) to produce images that exhibit the target domain's style while retaining the source domain's identity information.

Table 1. Properties of common vehicle Re-ID datasets

Dataset	*Images*	*Identities*	*Cameras*	*Evaluation*
VeRi-776	49,360	776	20	Handcrafted
Vehicle-ID	221,763	26,267	12	Handcrafted
CompCars	214,345	1,687	--	Handcrafted
CityFlow	229,680	666	40	SSD, YOLO, R-CNN
VERI-Wild	416,314	26,267	174	YOLO-v2 [2]
VRIC	60,430	5,622	120	Handcrafted

3. Datasets and performance evaluation

This section introduces a popular dataset for evaluating existing deep learning-based vehicle re-ID methods and briefly discusses common evaluation metrics.

3.1. Datasets

Vehicle re-ID technology has developed significantly due to its strong support by access to many large datasets (as shown in Figure 4 and Table 1). In recent years, several available datasets for vehicle re-ID have been released. Researchers and developers working on vehicle re-ID algorithms use the datasets to train and test their models. The ultimate goal is to create algorithms that can accurately match the same vehicle across camera views or at different times, even under challenging conditions.

VeRi-776 [66] is a popular dataset specifically designed for research in vehicle Re-ID. It contains 49753 images from 20 cameras with 776 different cars, each identity corresponding to a unique vehicle. The dataset includes photos from several front, rear, and side directions. Researchers widely use the VeRi-776 dataset to develop and evaluate vehicle Re-ID algorithms.

Vehicle-ID [67] dataset is another important dataset commonly used for research in vehicle Re-ID. The Vehicle-ID has 26,267 vehicles and 221,763 images captured from various cameras in various scenarios. Like other vehicle Re-ID datasets, Vehicle-ID presents challenges such as occlusions, variations in lighting, and changes in vehicle orientation, making it suitable for evaluating the robustness and generalization of Re-ID algorithms.

CompCars [68] dataset containing 1,687 vehicles and 214,345 images. CompCars Contains vehicle images captured from different viewpoints and under varying conditions, simulating real-world scenarios where vehicles must be tracked across different camera angles or locations.

VERI-Wild [69] dataset is an extensive vehicle Re-ID dataset published in 2019. It contains 416,314 training images from 26,267 vehicles captured from 174 real surveillance cameras.

The VRIC [70] dataset was proposed in 2018 for object detection and vehicle Re-ID in traffic scenes. It comprises 60,430 images depicting 5,622 distinct vehicle identities captured by 60 diverse cameras at various road traffic locations during diurnal and nocturnal periods.

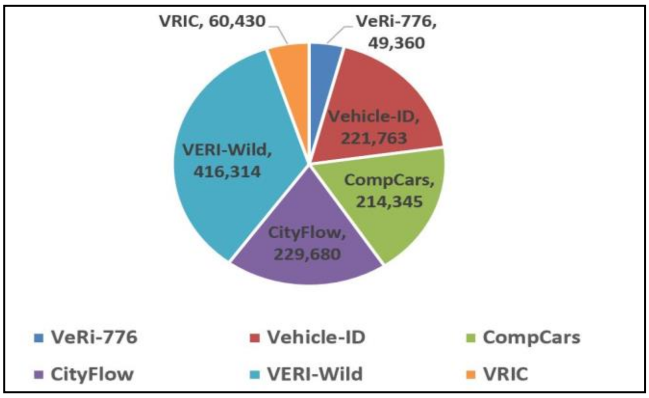

Fig. 4 Shows the total number of images in each vehicle Re-ID dataset.

3.2. Evaluation metrics

Evaluation metrics evaluate the performance and effectiveness of various systems, models, algorithms, or processes in various fields, including machine learning, data science, natural language processing, computer vision, and more. These metrics help quantify how well a particular system or method performs its intended task. Different tasks and domains may require specific evaluation metrics tailored to their unique characteristics. To evaluate the performance of vehicle Re-ID systems, mean average precision (mAP) and cumulative matching characteristics (CMC) curves.

The cumulative matching characteristic (CMC) [71] curve is a common evaluation metric used in Re-ID tasks, including vehicle and person Re-ID. It measures the performance of an algorithm in matching or re-identifying individuals or objects across different cameras or frames by measuring the cumulative percentage of correct matches at different ranks. The CMC curve provides insights into how well an algorithm performs in re-identifying vehicles or objects. The higher the curve's values at lower ranks (e.g., Rank-1, Rank-5), the better the algorithm's performance in identifying the correct matches early in the ranking list. A steeper curve indicates more effective Re-ID at lower ranks.

4. The state-of-the-art for deep learning-based vehicle Re-ID

Table 2 presents a comparison of several Re-ID approaches from 2018 to date. The test datasets encompassed are VeRi-776 and Vehicle-ID, and the evaluation methods employed to assess accuracy encompass mAP (mean Average Precision) and Rank1. mAP represents the mean accuracy across all query images for each individual query image, and Rank1 signifies the mean accuracy of the initial image that corresponds with all queried images.

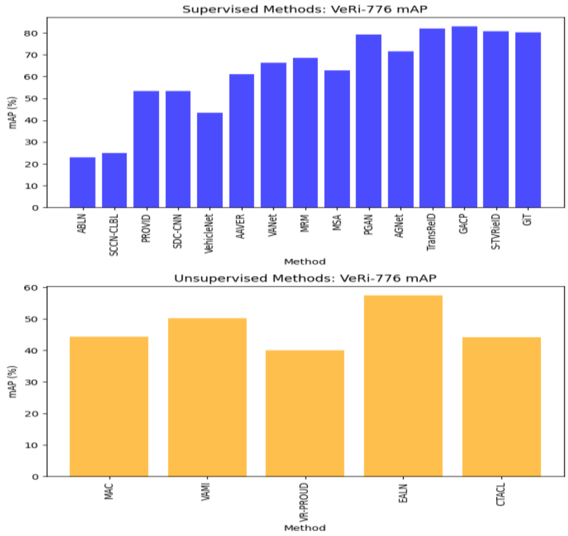

Fig.5 Comparison of performance mAP for Supervised and Unsupervised Vehicle Re-ID methods on the VeRi-776 Dataset.

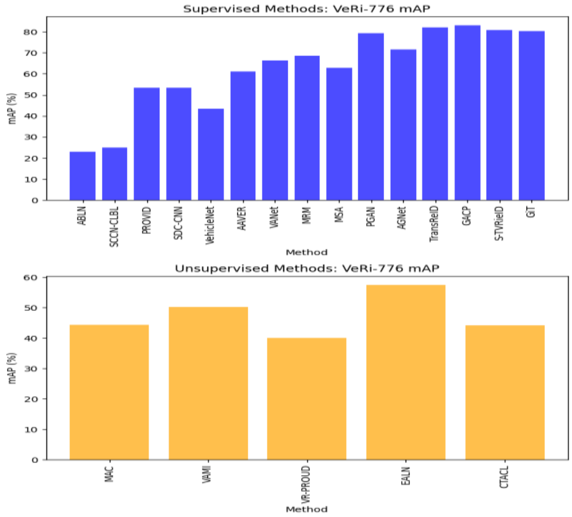

Fig.6 Comparison of Rank1 Accuracy for Supervised and Unsupervised Vehicle Re-ID methods on the VeRi-776 Dataset.

The results in Table 2 compare the performance of various vehicle Re-ID methods across the VeRi-776 and Vehicle-ID datasets, highlighting the distinction between supervised and unsupervised approaches. The initial 15 entries in the table compare the performance of supervised methods, while the final five entries focus on the performance comparison of unsupervised methods. Supervised methods generally outperform unsupervised ones, with top performers like Trans-ReID and GiT achieving Rank1 accuracies as high as 97.1% and 96.86% on VeRi-776 and 85.2% and 84.65% on Vehicle-ID, respectively. These methods leverage attention mechanisms and vision transformers, which are particularly effective. On the other hand, unsupervised methods, while lagging behind, show promising advancements, with EALN leading in this category, reaching 84.39% Rank1 on VeRi-776 and 75.11% on Vehicle-ID. The narrowing gap between supervised and unsupervised performance, especially with EALN, suggests ongoing improvements in unsupervised learning techniques. Overall, the results emphasize the effectiveness of attention mechanisms and vision transformers in supervised learning and indicate the potential of unsupervised methods for scenarios where labeled data is scarce. As shown in Figure 5 and Figure 6, supervised methods generally outperform unsupervised methods, with TransReID and GiT achieving the highest Rank1 accuracy of 97.1% and 96.86%, respectively. Among unsupervised methods, EALN performs the best with a Rank1 accuracy of 84.39%, indicating that while unsupervised methods lag behind, they can still achieve competitive results.

5. Challenges and Recent Achievements

Vehicle Re-ID is a challenging computer vision task that involves matching or re-identifying vehicles across different cameras or frames in surveillance and traffic monitoring systems[72, 73]. Several challenges make this task difficult, including viewpoint variations, occlusions, lighting changes, and variations in vehicle appearance, as shown in Figure 7. In this section, we will focus on reviewing the challenges of Vehicle Re-ID and providing details of progress made on each of the challenges in recent years.

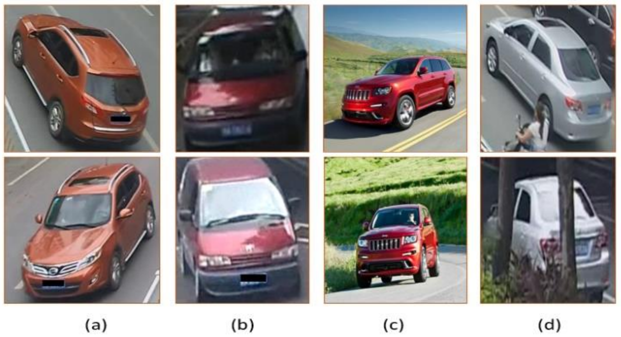

Fig. 7 Illustrates the challenges of vehicle Re-ID tasks: (a) Viewpoint variations, (b) Varying Illumination & Shadows, (c) Similar appearance, and (d) Occlusions.

5.1. Viewpoint variations

The main challenge in developing vehicle Re-ID solutions lies in viewpoint, as distinct views of vehicles captured by non-overlapping cameras encompass diverse information. Whether it involves identifying specific view angles or extracting view-generic and view-invariant vehicle features, these approaches are essential for minimizing the distance between vehicles within the same class and maximizing the distance between different classes. Figure 7-a Illustrates the viewpoint variation challenge. To deal with viewpoint variation, several methods have been developed to solve this challenge.

Deep Learning Techniques: Yi Zhou et al. [3] proposed two collaborative deep networks, namely the CLBL (CNN-LSTM Bi-directional Loop) and SCCN (Spatially

Concatenated Conv-Net), to explore the multi-viewpoint vehicle Re-ID task. Their method leverages the significant benefits of CNN and LSTM (Long short-term memory) to learn transformations across different vehicle viewpoints. Ruihang Chu et al. [13] proposed a viewpoint-aware metric learning method named VA-Net (viewpoint-aware network) to tackle challenges of different viewpoints and similar viewpoints in two feature spaces. Their experiments used GoogLeNet [74] as a backbone for cross-entropy loss. The VA-Net system has categorized vehicle Re-ID into two distinct scenarios: Re-ID from different viewpoints and Re-ID from similar viewpoints. In [64], viewpoint adaptation learning was proposed using a cross-view distance metric approach to tackle the multiple viewpoints challenge vehicle Re-ID. This approach comprises two modules: a VA-Net (viewpoint adaptation network) module and the utilization of a cross-view distance metric module. The approach integrates multiple levels of features to achieve a powerful training model.

Attention-based Methods: attention-based deep learning methods offer a promising avenue for addressing the challenges posed by viewpoint variations in vehicle Re-ID. By enabling models to focus on the most distinctive and reliable features of vehicles, these methods improve the accuracy and robustness of Re-ID systems. Wu et al. [6] introduced an attention mechanism for the multi-camera surround-view scenario to overcome the challenge of different viewpoints for the same vehicle through multiple cameras. To acquire distinctive features that are not influenced by various environmental factors, a partially guided attention-based approach was proposed in [17].

Table 2. The performance comparison of vehicle Re-ID methods

Method	*Description*	*VeRi-776*		*Vehicle-ID*	
		Rank1	*mAP*	*Rank1*	*mAP*
ABLN [1]	LSTM network	58.14	22.91	52.63	-
SCCN-CLBL [3]	CNN baseline, LSTM	60.83	25.12	48.63	-
PROVID [5]	Metric Learning	81.56	53.42	-	-
SDC-CNN [7]	Metric Learning	83.49	53.45	50.16	56.76
VehicleNet [8]	Representation Learning	79.48	43.47	83.37	47.56
AAVER [9]	Attention mechanism	88.97	61.18	74.69	-
VANet [13]	Metric Learning	89.78	66.34	83.26	-
MRM [14]	Local Features	91.77	68.55	68.83	71.74
MSA [15]	Attention mechanism	92.07	62.89	77.55	80.31
PGAN [17]	Attention mechanism	96.5	79.3	77.8	83.9
AGNet [18]	Local feature	95.61	71.59	65.74	69.66
TransReID [20]	Attention mechanism	97.1	82.0	85.2	-
GACP [22]	Attention mechanism	96.1	83.0	-	-
S-TVReID [23]	Vision transformer	96.4	80.8	84.3	-
GiT [25]	Graph Network, Vision transformer	96.86	80.34	84.65	90.12
MAC [26]	clustering	72.40	44.29	54.27	56.18
VAMI [28]	GANs , Attention Mechanisms	77.03	50.13	63.12	-
VR-PROUD [33]	CNN + unsupervised Learning	83.19	40.05	71.45	-
EALN [35]	Unsupervised Learning	84.39	57.44	75.11	77.5
CTACL [36]	Self-supervised contrastive learning, Softmax cross-entropy	81.6	44.2	-	-

Innovation in this area is imperative to fully harness attention mechanisms' potential and advance the state-of-the-art in-vehicle Re-ID technologies. As research progresses, we can anticipate more nuanced attention models that cater to the complex and dynamic demands of real-world surveillance and traffic management systems.

An unsupervised viewpoint-aware clustering approach for vehicle re-ID was introduced in [75] by analyzing the similarity problem of vehicle comparison and exploring progressive clustering by partitioning the training set into distinct subsets in compliance with the viewpoint. This approach is founded upon the observation that images of vehicles captured from neighboring perspectives typically exhibit a significant level of shared visual characteristics. Consequently, they proposed merging these adjacent views by leveraging their similarity.

5.2. Varying Illumination & Shadows

Varying illumination and shadows can significantly complicate the task of vehicle Re-ID for several reasons, including Contrast and Brightness Fluctuations, Variable Appearance, Reflections, Low-light Conditions, and Transitions between Cameras [5, 76]. Figure 7-b demonstrates the Varying Illumination & Shadows challenge. Different lighting conditions can change the appearance of a vehicle's color and texture. For instance, a vehicle that appears blue under bright sunlight might look black or dark blue under streetlights or during twilight. Also, the contrast and brightness of the image may vary with illumination, potentially obscuring distinguishing features or causing cameras to overexpose or underexpose parts of the vehicle. To overcome these challenges, several strategies can be employed.

CNN-based methods: Deep learning techniques have effectively overcome the challenge of varying lighting and shadows in vehicle Re-ID, especially due to their ability to learn complex, high-dimensional features from data.

Attention-based Techniques: Shao Liu et al. [77] presented a Self-Attention method to address the challenge of varying Illumination in vehicle Re-ID to achieve attention consistency among low-light images. This work utilized Resnet50 [78] and VehicleNet [8] as backbones for producing image embedding of inputs. They experimentally concluded that the lighting environment affects the within-class variation and performance of the Re-ID model.

5.3. Occlusions

Occlusions present a significant challenge in vehicle Re-ID, as depicted in Figure 7-d. An occlusion occurs when part or all of a vehicle is obscured or covered by another object. This obstruction makes it difficult to recognize the vehicle based on its complete visual appearance.

CNN-based methods: Liu, Xinchen, et al. [79] proposed a cross-segment inference network directed at analysis method named PCR-Net (Parsing guided Cross part Reasoning Network). The method can address the challenges of partial occlusion, which delves into the precise parsing of vehicle components to uncover the connections between them and acquires distinctive local characteristics for the purpose of vehicle Re-ID; the deep-CNN was used for the global branch of the PCR-Net and GCN for local information part. Yuming Liu et al. [80] Proposed a framework for vehicle Re-ID by partitioning the covered and closed vehicle pair trajectories and recalculating the similarity of the sub-trajectories. The proposed approach recalculates the similarity of the complete trajectories, which can improve occlusion operations and reduce the challenge in single-camera tracking.

Attention-based methods: Eckstein et al. [81] addressed the occlusion by relying on temporal attention scores, prioritizing video frames exhibiting minimal occlusion.

5.4. Similar appearance

One significant challenge in vehicle Re-ID is distinguishing between vehicles with similar appearances but different identities (Figure 7-c). This is often encountered when multiple vehicles of the same make, model, and color are in a monitored area. Addressing this challenge is crucial for the success of a vehicle Re-ID system, especially in densely populated urban environments where vehicle variety might be limited.

CNN-based methods: Hongye Liu et al. [67] handled the challenges of a similar vehicle by Accurate vehicle search and learning deep CNN.

*Attention-based methods***:** To address similar appearance challenges, various attention mechanism methods have been developed to enhance the performance of vehicle Re-ID systems. Jiang et al. [82] proposed an attention-based GRA-Net (Global Reference Attention Network) that significantly helps distinguish between different compounds having similar appearances. In [83], An attention-based method was proposed to address the challenge of inter-class similarity and environmental interference in complex scenes. By focusing on the detailed distinguishing features of vehicles, this approach improves the accuracy of vehicle Re-ID in environments with varied and challenging conditions. Liu et al. [84] presented the APA-Net (Attentive Part-Based Alignment Network) Network to learn robust, diverse, and discriminative features for vehicle Re-ID, addressing the issue of attention misalignment which is often a shortfall in conventional attention-based vehicle Re-ID networks.

In summary, these approaches highlight the various approaches taken to enhance vehicle Re-ID systems, particularly in overcoming challenges posed by vehicles with similar appearances and varying environmental conditions. The integration of attention mechanisms in these methods demonstrates their effectiveness in improving the accuracy and reliability of vehicle Re-ID systems.

6. Conclusion

This paper provides a comprehensive overview of the recent advances in deep learning-based vehicle Re-ID techniques, highlighting their increasing accuracy and efficiency. We discussed various challenges, including Viewpoint variations, Varying Illumination, occlusion, and similar appearance, which remain significant hurdles in achieving optimal performance.

In the future, vehicle Re-ID is expected to continue to evolve with advances in deep learning, machine learning, and artificial intelligence. This development is likely to include incorporating more sophisticated models and improving the handling of real-world fluctuations. In addition, the increasing focus on smart cities and intelligent transportation systems will further drive the development of more advanced and efficient vehicle Re-ID systems.

While deep learning techniques have significantly improved vehicle Re-ID, this field continues to evolve and faces ongoing challenges. Solving these challenges and developing more advanced technologies will be crucial in realizing the full potential of vehicle Re-ID systems in enhancing urban traffic management and public security.

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