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PEDESTRIAN TRACKING AND VEHICLE RE-IDENTIFICATION

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Abstract
Pedestrian and vehicle re-identification represent vital facets of computer vision, shaping the landscape of surveillance, security, and transportation systems. This detailed abstract delves into the substantial role and recent advancements in re-identification techniques for pedestrians and vehicles, illuminating the complexities, applications, and ongoing research in this field. Pedestrian re-identification involves the challenging task of recognizing and tracking individuals as they traverse various camera viewpoints, often within densely populated areas. Vehicle re-identification, similarly, focuses on identifying and monitoring vehicles as they move through an array of surveillance points. These capabilities bear far-reaching implications, from enhancing urban security and crowd management to optimizing traffic flow and border control. A significant breakthrough in recent years has been the adoption of deep learning methodologies, particularly convolutional neural networks (CNNs), to tackle pedestrian and vehicle re-identification challenges. CNNs excel in learning discriminative features from images or video frames, enhancing the precision and robustness of identification processes. Such neural networks have enabled more accurate matching of individuals or vehicles across different camera angles and lighting conditions, a crucial requirement for real-world applications. However, the path to effective re-identification remains paved with obstacles. Occlusions, pose variations, and the scalability of re-identification algorithms in extensive surveillance networks continue to challenge researchers and engineers. The field is also grappling with ethical and privacy considerations, as the deployment of re-identification systems raises concerns about data security and individual privacy. The extensive exploration of pedestrian and vehicle re-identification techniques. In the subsequent discussion, we will delve into the manifold applications, recent innovations, and ongoing efforts to surmount the persisting challenges in these pivotal domains of computer vision. Furthermore, we will explore the ethical dimensions that shape the responsible development and deployment of re-identification systems in an increasingly interconnected world.
Keywords: Pedestrians Detection, Tracking, Re-Identification, Unmanned Aerial Vehicles, Drones, Surveillance, license plate recognition, video surveillance, feature extraction

Introduction

In artificial intelligence, Multiple Object Tracking (MOT) refers to the task of locating objects in a scene and maintaining their trajectories throughout the entire video. It is an essential task for a broad range of computer vision applications such as surveillance, and autonomous driving. Pedestrians are among the most interesting subjects to track in public area for many purposes such as safety and security. Therefore, lately, there has been a lot of research attention to pedestrian tracking.

Pedestrian and vehicle re-identification represent crucial facets of computer vision, revolutionizing surveillance, security, and transportation systems. In this rapidly evolving field, the challenge lies in recognizing and tracking individuals and vehicles across diverse camera viewpoints and conditions. These capabilities have far-reaching implications, from bolstering urban safety and managing crowds to optimizing traffic flow and enhancing border control. The adoption of deep learning, particularly convolutional neural networks (CNNs), has propelled advances in re-identification accuracy. However, obstacles like occlusions, pose variations, and ethical considerations continue to shape the landscape. This article delves into the world of pedestrian and vehicle re-identification, exploring applications, innovations, and challenges while addressing ethical dimensions in an interconnected world. The realm of computer vision, pedestrian and vehicle re-identification have emerged as pivotal fields, reshaping the landscape of surveillance, security, and transportation systems. These domains involve the task of identifying and tracking individuals and vehicles across diverse camera viewpoints, lighting conditions, and scenarios. The significance of this lies in its extensive applications, ranging from enhancing urban safety and crowd management to optimizing traffic control and fortifying border security. The crux of pedestrian re-identification revolves around recognizing and tracking people as they traverse complex environments, such as crowded streets and busy intersections. This capability is invaluable in scenarios where maintaining the identity of individuals across different camera feeds is essential, such as tracking potential suspects or ensuring public safety during large events. Similarly, vehicle re-identification is concerned with the precise identification and continuous monitoring of vehicles as they move through various surveillance points. This can be critical in applications like traffic monitoring, toll collection, and border control, where the ability to distinguish and track vehicles efficiently is essential for seamless operations.

In recent years, a significant leap in re-identification techniques has been facilitated by the widespread adoption of deep learning, notably convolutional neural networks (CNNs). These neural networks excel at learning intricate patterns and features from images or video frames, greatly enhancing the accuracy and robustness of identification processes. The result is a more reliable and efficient system capable of matching individuals or vehicles accurately across different camera angles and environmental conditions. However, the journey toward effective re-identification remains challenging. Issues such as occlusions (when objects partially or completely block the view of the target), pose variations (changes in the pose or position of a person or vehicle), and the scalability of re-identification algorithms in vast surveillance networks present formidable obstacles. Moreover, ethical and privacy concerns loom large as the deployment of re-identification systems sparks debates about data security, individual privacy, and potential misuse.

The challenges of re-identifying vehicles and persons have significant differences. For wide area video surveillance on humans, the same identity viewed from a different pose angle usually looks fairly alike. The shape of the detection remains upright and the colour information, predominantly extracted from articles of clothing, is of a similar pattern. The same condition cannot be satisfied for vehicles. Colour information can become far more distorted in different lighting due to the reflectiveness of the body of a car. The shape information of a car viewed from the front is significantly different than that viewed from a 45° or 90° angle. On the contrary, many high-end vehicle re-ID algorithms use license plate information, which is not applicable in the human domain. Moreover, pedestrians are more likely to undergo significant changes over time or viewpoint, e.g. a person's appearance is greatly altered after they put on a coat. In general, changes to vehicles between viewpoints are high variance but predictable whereas the change in a person's colour representation is usually lower variance but prone to much more extreme outliers. We propose that there are underlying principles of re-ID that hold regardless of the composition of the object worked upon. Unifying person and vehicle re-ID allows us to explore and discover these underlying principles, precisely because they are so different.

Most machine learning tracking and re-identification applications are heavily affected by image acquisition systems such as static cameras and the cost of collecting data. Unmanned aerial vehicles (UAV's), which enable a low-cost way of data collection while covering broad and difficult-to-reach regions, have recently been recognized as a feasible alternative for monitoring public spaces. The advancements in UAV's have benefited MOT, particularly pedestrian tracking and re-identification, since it gives a viable solution to solve numerous challenges such as occlusion, moving cameras, and difficult-to-reach locations. Compared to static cameras, UAV's are flexible enough to adapt their emplacement location and direction in the 3D space.

Due to growing global population, commercial activities have been extensively increasing, which leads everyone to access road transportation as a source of mobility. Due to easy accessibility of road transportation system, traffic on roads is massively increasing that not only creates the problem of high traffic congestion but also a drastic increase in carbon dioxide emissions. Along with these issues, road accident risks and the overall transportation complexity increases as well. Therefore, a smooth transportation source and medium is always required for growing commercial activities. Furthermore, traffic management authorities are facing hectic challenges to maintain an undisturbed transportation system. Their task includes tracking the suspicious vehicle, handling traffic jam, and to check whether the vehicle is registered or not. Maintaining undisturbed transportation becomes harder when a large number of vehicles are on the roads.

Intelligent Transportation System

Transport is essential for the daily routine functioning of the economy and the society. Over the past few decades, there is huge development, deployment, and growth in the transport system and have notable effect of development in society and daily life. Therefore, transportation should be redefined as ITS. Currently, not only mechanical and engineering fields are doing research and development for better transportation facility, but computer science related concepts are also playing major role for instance, artificial intelligence (AI), communication, machine learning (ML), internet and so many other emerging technologies.

Due to traffic problems in China, the average speed of vehicle has been decreased to 20 km/h, even in some areas between 7 and 8 km/h. Such low speed of vehicles for a long time on roads is a threat for the natural environment of the world like exhaust emissions that deteriorate air quality. In order to deal traffic problems and alleviate the pressure of vehicles on roads, the governments are investing too much on research and ITS development. ITS based infrastructure strengthens the relationship between people, vehicles, and road networks.

ITS have the capability to enhance the performance of current transportation system and make it efficient, safe, comfortable as well as reduces harmful environmental consequences. ITS based real-time applications include electronic payment systems, traffic management systems, emergency vehicle pre-emption management system, advanced vehicle control systems, weather precautionary measures management system, and commercial vehicle operations. Applications of ITS now regularly deployed, such as closed-circuit television surveillance, automatic car parking, electronic toll collection, border control, and in-car navigation equipment. Therefore, an ITS is needed to analyze the recorded video, control, maintain and communicate to ground transport and improve mobility and manage problems efficiently. Furthermore, Figure 1 demonstrates the ITS based environment.

Video Surveillance

In metropolitan cities, cameras are widely adopted in numerous areas to monitor activities but most of the current video surveillance systems provides the facilities like capture, storage and distribute video, while leaves unwanted event detection task totally on human operators. Human operator-based monitoring of the surveillance system is not as efficient and a very labor-intensive task, as shown in Figure 2. It requires full visual attention by watching the video in control room and it is very difficult for single person as everyday tasks. Specifically, the ability to focus and react to occasionally occurring activities that require full attention. Furthermore, millions of hours of video data generated by multiple cameras over surveillance network require large number of operators for the task. It is almost infeasible, inefficient and costly to obtain real-time prevention

Due to digital cameras and the advent of powerful computing resources, automatic video analysis become possible and more and more common in video surveillance applications [4], thus reduces the labor cost. Practically, the objective of automatic video analysis for safety, security, and surveillance is to detect automatically unwanted events or situations that need security attention. Automated video analysis not only process the data faster but also significantly improve the ability to preempt incidents on time. Augmenting security staff with automatic processing increases their efficiency and effectiveness. For the posterior mode, searching a specific vehicle in hundreds of hours of camera recorded video footage needs large number of officers to do this task and takes a lot of time. Automated content-based video retrieval reproducing and assisting human analysis on recorded videos largely enhances forensic capabilities. Furthermore, the surveillance systems application's main goal is to develop intelligent systems that automate the human decision-making mechanism.

View of manually traffic monitoring at control room.

Re-Identification

In a surveillance camera without overlapping vision, re-id is defined as a task to identify objects' captured images taken from different camera networks. It is used to know whether the object image captured by multiple surveillance cameras matches the same object or a different image of the object. Object re-id technology has a significant role in multi-object tracking, intelligent monitoring, and other fields. Recently, re-id gained extensive attention in the computer vision research community. The main application fields of an object re-id are vehicle re-id and person re-id.

Vehicle Re-identification

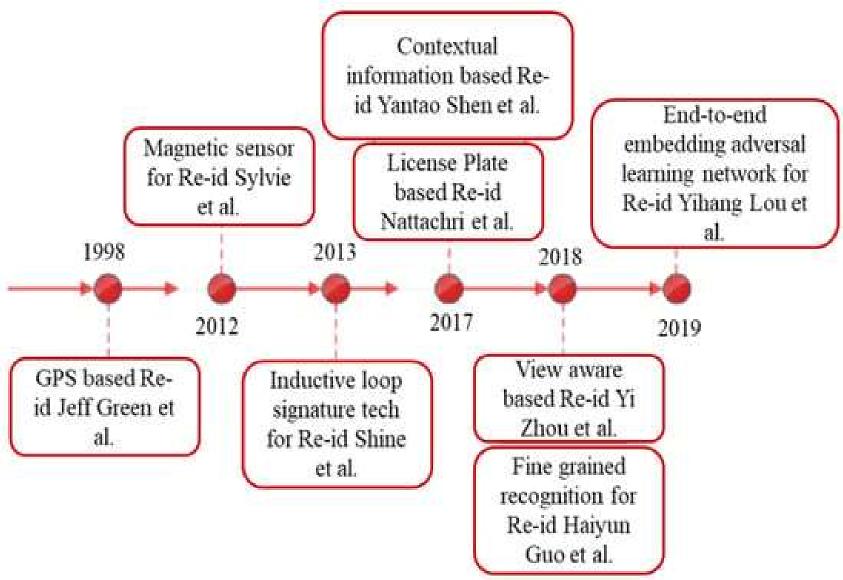
Similar to person re-id, vehicle re-id is also a demanding task in camera surveillance. Aim of vehicle re-id is to match vehicle images with already captured vehicle images over the camera network. However, due to surveillance cameras on the roads for smart cities and traffic management, the demand to perform vehicle search from the gallery set is increased. Vehicle re-id is similar to several other applications, such as person re-id, behavior analysis, cross-camera tracking, vehicle classification, object retrieval, object recognition, and so on.

- To understand designing the vehicle re-id system, we analyze how a person re-identifies the vehicle. A person re-identifies vehicle by keeping in mind some characteristics like unique feature, color, size etc., our brain and eyes are learned to detect and identify different objects.
- Vehicle Re-Identification Practical Application
- There are many significant real-world applications where vehicle re-id system can be utilized and satisfies the great needs of our practical life. However, some major applications are briefly discussed as follows:

- Suspicious vehicle search: Most of the time terrorists use vehicle for their criminal activities and soon leave that spot on vehicles. It is very difficult to fast search suspicious vehicle manually from surveillance camera.
- Cross camera vehicle tracking: In vehicle race sports, some of the viewers on television wish to watch specific vehicle. With vehicle re-id system broadcaster can only focus on that specific vehicle when it comes in the field of view of surveillance camera network.
- Automatic toll collection: Vehicle re-id system can be used at toll gates to identify vehicle type like small medium and large and charge the toll rate accordingly. Automatic toll collection reduces delay and improves the toll collection performance by saving travelers time and fuel consumption.
- Road access restriction management: In big cities, heavy vehicles like trucks are not permitted in the daytime, or some of the vehicles with specific license plate number are permitted on specific days to avoid congestion in city or officially authorized vehicles can enter in city.
- Parking lot access: vehicle re-id system can be deployed at the gate of parking lot of different places like head offices, and residential societies. So only authorized vehicles are allowed to park.
- Traffic behavior analysis: Vehicle re-id can be used to examine the traffic pressure on different roads at different times, such as peak hours calculation or particular vehicle type behavior.
- Vehicle counting: System can be useful to count a certain type of vehicle.
- Speed restriction management system: Vehicle re-id system can be utilized to calculate the vehicle's average speed when it is crossing from two subsequent surveillance camera positions.
- Travel time estimation: Travel time information is important for a person who is traveling on road, it can be calculated when a vehicle is passing in between consecutive surveillance cameras.
- Traffic congestion estimation: By knowing the number of vehicles flow from one point to another point within a specific time period using vehicle re-id system, we can estimate traffic congestion at the common spot from where all vehicles may cross.
- Delay estimation: Specific commercial vehicle delay can be estimated after predicting traffic congestion on the rout that vehicle follows.
- Highway data collection: Highway data can be collected through surveillance cameras that are installed on roadsides and that data can be used for any purposes after processing and analyzing at the traffic control center.
- Traffic management systems (TMS): Vehicle re-id is an integral part of TMS, it helps to increase transportation performance, for instance, safe movement, flow, and economic productivity. TMS gathers the real-time data from the surveillance cameras network and streams into the Transportation Management Center (TMC) for data processing and analyzing.
- Weather precautionary measures: When specific vehicle is identified that may be affected by weather, then traffic management systems notify that vehicle about weather conditions like wind velocity, severe weather etc.

- Emergency vehicle pre-emption: If any suspicious vehicle is identified at any event or road then vehicle pre-emption system passes messages towards lifesaving agencies such as security, firefighters, ambulance, traffic police, etc. to reach in time and stabilize the scene. With this system, we can maximize safety and minimize response time.
- Access control: Vehicle re-id system can be implemented for providing safety and security, logging and event management. With the implementation of the system only authorized members can get an automatic door opening facility, which helps guards on duty.
- Border control: Vehicle re-id system can be adopted at different check posts to minimize illegal vehicle border crossing. Vehicle re-id system can provide vehicle and owner's information as it approaches security officer after identifying the vehicle. Commonly these illegal vehicles are involved in cargo smuggling.
- Traffic signal light: When the traffic light is red and any vehicle crosses stop line, the vehicle re-id system can be implemented to identify that vehicle for fine.
- Vehicle retrieval: In this case, re-id is associated with a recognition task. The specific query with a target vehicle is provided, and all the related vehicles are searched in the database. The re-id task is thus employed for image retrieval and usually provides ranked lists, similarly related items, and so on.

Two ways for writing surveys can be found in the object re-id literature; first way gives a deep insight into methodologies, whereas the second way covers the overall perspective related to the problem. This survey includes both methodologies and overall perspective of vehicle re-id literature. We also review the recent development of vision-based vehicle re-id along with other technologies. In addition, this survey draws a timeline to introduce important milestones for vehicle re-id.

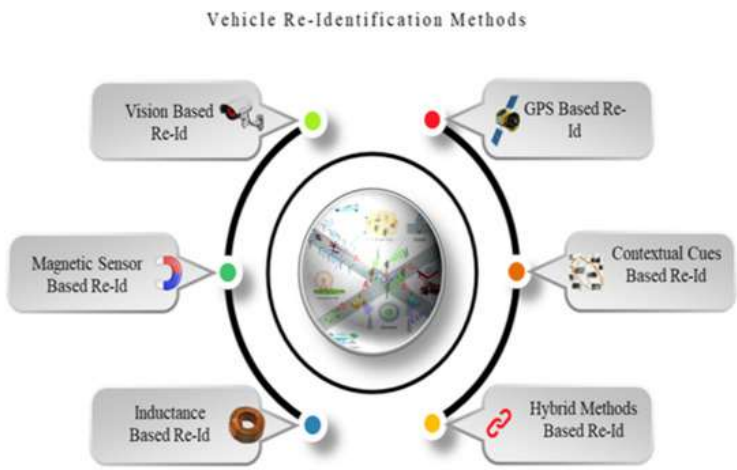


Milestones existing re-id approaches in the Vehicle re-id history

Related to work

Methods Used for Vehicle Re-Identification

Traditionally different traffic sensors are adopted to know the vehicle presence, volume, occupancy, and speed data. Nowadays, new sensor-based technology is adopted to get more information like origin-destination estimation, travel time and other travel information applications.



Vehicle re-id methods

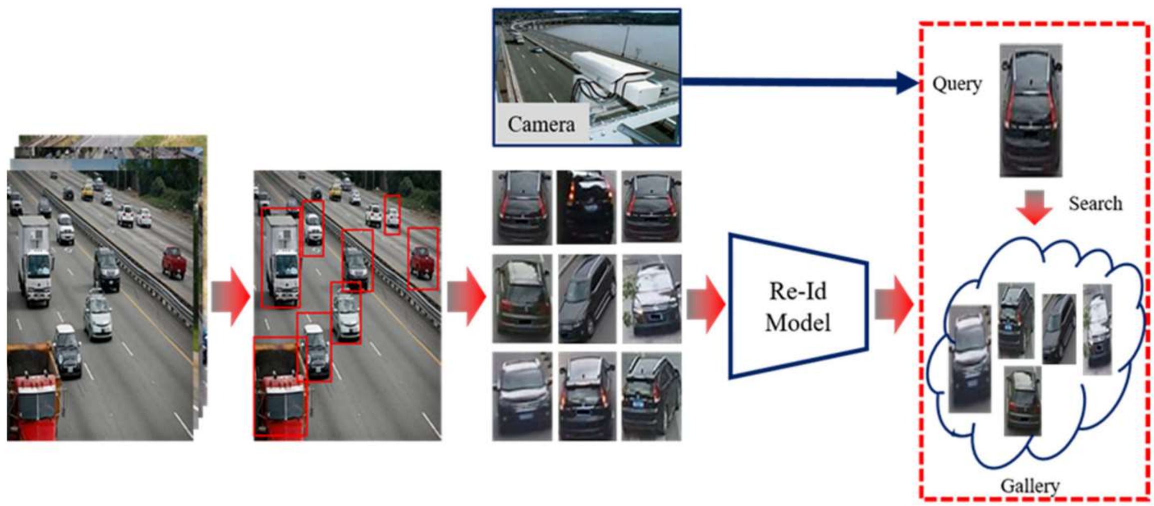
Magnetic Sensor-Based Vehicle Re-Identification
An electromagnetic field is used to detect the vehicle, when it crosses and it is used to provide occupancies, counts, and vehicle speed. However, vehicles are made up of metal. It disrupts the magnetic field, so magnetic signature regenerated by one vehicle is different from the other vehicle. This approach helps in re-identifying a specific vehicle. Moreover, for ITS the Berkeley's company sells magnetic sensors with the name "Sensys Network". A straight-line re-id rat is 50%, and the approach reduces the magnetic signature peak value sequence for calculating the signature distance to prevent vehicle speed dependency. For real-time vehicle re-id processing unit is associated to thousands of magnetic sensor nodes and a large number of magnetic sensors that generate massive data streams, and to deal with real-time data stream mining, high-performance FPGAs and low-performance microcontroller are used. Sylvie Charbonnier et al. studied various approaches for vehicle re-id by adopting vehicle tridimensional magnetic signature measured with sensor, when car passes sensor and changes in the magnetic field were induced and measured in three different directions like X, Y, Z. Rene O. Sanchez et al. investigated vehicle re-id approaches by using wireless magnetic sensors and compares vehicle magnetic signatures to overcome the limitations of system while vehicle is stopped or moving slow at detection station.

Inductive Loop-Based Vehicle Re-Identification
Vehicle can be re-identified using inductive loops embedded in the road surface for the detection of vehicle. From those loops, a fingerprint is captured for every car passing by. The travel time can be determined when those fingerprints or certain aspects of them coming from different locations are compared with each other. Designed a real-time inductive loop signature-based vehicle re-id method named RTREID-2M. Inductive signature is used for

vehicle re-id and much efforts have been done to utilize inductive loop signature technology. Inductive signature-based vehicle re-id algorithms identify specific vehicle at downstream detection station by matching the inductive signature at upstream detection station, considering that vehicle have same signature by crossing different loop detection stations. Vehicle re-id researchers have proposed several algorithms like optimization, piecewise slope rate (PSR) matching, lexicographic and blind deconvolution [29], all these proposed approaches are for raw signature processing, signature feature extraction, and vehicle matching.

Vision-Based Vehicle Re-Identification

In computer vision, the aim of vehicle re-id is to identify specific vehicle that appeared over in multiple cameras network. The large surveillance camera network is deployed in different areas of public places like hospitals, parks, colleges, roads, and other areas. It is also difficult and tiresome job for security officers to track targeted or specific vehicle over multiple camera network manually.



The flow of designing a practical vehicle re-id system, including five main steps

Vision-Based State-of-the-Art Vehicle Re-Identification Approaches

Vision-based methods focus on examining robust feature representations to calculate the distance between features of two-vehicle images and vehicles with the same class have a low distance otherwise high. However, vehicle features are difficult to distinguish when a captured vehicle image consists of similar colors and pose. In this section gives an overview of recent works on computer vision-based methods for vehicle re-id problem. Several impressive vision-based methods have been proposed to improve vehicle re-id performance either by modifying the existing DL architectures or by designing a new deep neural network (DNN). Generally speaking, eight different techniques have been employed in this research area: (A) Feature representation for vehicle re-id, (B) Similarity metric for vehicle re-id, (C) Traditional machine learning-based vehicle re-id, (D) View-aware-based vehicle re-id, (E) Fine-grained visual recognition-based vehicle re-id, (F) Generative adversarial network-based vehicle re-id, (G) Attention mechanism, (H) License plate-based vehicle re-id.

Challenges Regarding Vehicle Re-Identification

The vehicle re-id is among an essential and challenging task, and it is defined as, either any specific vehicle captured in one camera has already appeared over multiple camera network or not. With the increasing need for automated video analysis, the vehicle re-id receives increasing attention these days in the computer vision research community. Therefore, some key factor and their effects on performance are explained following.

- Insufficient data: For vehicle re-id systems each single image should match with gallery images, so it is very hard to get sufficient data for good model learning of each intra-class variability. However, it is also major challenge that dataset should reflect the real-world surveillance, currently, most of the datasets available are consists of non-overlapping views with a limited number of cameras; as a result, datasets have few viewpoints with unchanged regulation, and most of the publicly available datasets are consists of limited instances and classes that influence the performances.
- Inter-class similarity: This problem arises due to different automobile manufacturing companies have a similar visual appearance, as a result, two different make, model, and type of vehicles looks similar from rear or front side.
- Intra-class variability: due to the unconstrained environment and viewpoint, the same vehicle looks different over different geographical locations of the surveillance camera network.
- Pose and viewpoint variations: Due to the camera calibration, viewing angle and location on the roadside, captured vehicle image appearance varies, and the same vehicle looks different and different looks same. A learned model on the rear pose of a vehicle will probably fail to detect a vehicle's front, side pose.

Future Advancements in Pedestrian and Vehicle Re-Identification:

As technology continues to evolve, pedestrian and vehicle re-identification will see further advancements and innovations. Here are some potential future developments in these fields:
Multi-Modal Fusion: Future re-identification systems may integrate data from various sensors, such as cameras, LiDAR, radar, and even thermal imaging, to enhance identification accuracy and robustness. Combining different modalities can help overcome challenges like occlusions and varying lighting conditions.

Generative Adversarial Networks (GANs): GANs have shown promise in generating realistic data. In re-identification, GANs can be used to augment training data, create synthetic challenging scenarios for testing, and even generate missing views of pedestrians or vehicles to aid in tracking.

Real-Time 3D Reconstruction: The adoption of 3D reconstruction techniques, combined with depth sensors, could enable real-time reconstruction of pedestrians and vehicles in 3D space. This information can be invaluable for tracking and re-identification, especially in crowded or complex environments.

Behavior Analysis: Beyond visual appearance, future systems may incorporate behavioral analysis. This could involve gait recognition for pedestrians or analyzing driving patterns for vehicles, adding another layer of identification and security.
Edge Computing: With the growing demand for real-time processing and privacy concerns, edge computing will become crucial. Re-identification systems may shift towards deploying AI models directly on cameras or sensors to reduce latency and minimize data transfer.

Continual Learning: Re-identification systems will likely incorporate continual learning approaches, allowing them to adapt and improve over time. This will be essential for handling changing environmental conditions and new challenges.

Explainable AI: Ethical considerations will drive the need for explainable AI in re-identification. Future systems may need to provide transparent explanations for their decisions, especially in critical applications like security and law enforcement.

Privacy-Preserving Techniques: To address privacy concerns, researchers will develop advanced privacy-preserving techniques that allow re-identification while protecting individual privacy. Differential privacy and secure multiparty computation are potential avenues for research.

Human-Machine Collaboration: Re-identification systems will increasingly collaborate with human operators. Machine learning models can assist human operators by flagging potential matches and anomalies, reducing the cognitive load on operators.

Standardized Datasets: The creation of standardized, diverse, and comprehensive datasets for benchmarking re-identification algorithms will be crucial. These datasets will facilitate fair comparisons and drive innovation in the field.

Regulatory Frameworks: Governments and regulatory bodies will likely introduce regulations and standards for the deployment of re-identification systems, particularly in public spaces. Compliance with these regulations will shape the development of these technologies.

Smart City Integration: Re-identification systems will play a significant role in smart city initiatives. They will be integrated into broader urban management systems, helping with traffic optimization, emergency response, and public safety.

Ethical and Bias Mitigation: Efforts to mitigate bias and ethical concerns in re-identification will be a continuous focus. Research will explore ways to reduce algorithmic biases and ensure fairness in system deployment.

These future advancements will not only enhance the capabilities of pedestrian and vehicle re-identification systems but also address the ethical, privacy, and regulatory challenges that come with their widespread adoption in an increasingly interconnected world.

Recommendation

To advance the field of pedestrian and vehicle re-identification responsibly, it is essential to foster interdisciplinary collaboration among computer vision experts, ethicists, legal professionals, and data scientists. Privacy should be a foundational principle in system design, with the implementation of privacy-preserving techniques and transparency mechanisms to protect individuals' identities. Clear ethical guidelines and codes of conduct must be established, particularly in sensitive contexts like law enforcement and surveillance, to ensure fairness and avoid bias. Compliance with evolving data privacy and surveillance regulations is paramount, and proactive engagement with regulatory bodies is encouraged. Standardized testing using common datasets and evaluation protocols should be promoted to enable fair comparisons and benchmarking. Continual evaluation, human oversight, and strategies to mitigate bias are crucial for maintaining system integrity and fairness. Additionally, education and awareness efforts should inform users and stakeholders about re-identification technology's capabilities and limitations, emphasizing its impact on privacy and civil liberties. Secure data handling practices, redundancy, and fail-safes are necessary in critical applications, and community engagement should involve public input and address concerns in deploying re-identification systems in public spaces. Researchers should uphold ethical principles in their studies, respecting informed consent and protecting participants' rights. Finally, continuous innovation and investment in research and development will ensure that re-identification systems evolve to address emerging challenges and opportunities in this rapidly advancing field.

Conclusion

In conclusion, pedestrian and vehicle re-identification represent dynamic and transformative fields within computer vision, with profound implications for surveillance, security, and transportation systems. The integration of deep learning methodologies, such as convolutional neural networks (CNNs), has significantly advanced the precision and robustness of these systems, enabling accurate identification and tracking across diverse camera viewpoints and conditions. However, this progress is accompanied by challenges related to privacy, bias, and ethical considerations, which necessitate careful navigation and responsible development

To move forward effectively, it is imperative to prioritize interdisciplinary collaboration, embracing expertise from various domains, and to embed privacy measures into the core of system design. Ethical guidelines, transparency mechanisms, and adherence to regulatory requirements are essential pillars of responsible deployment. Standardized testing, ongoing evaluation, and mitigation of bias contribute to the reliability and fairness of re-identification systems.

Moreover, the involvement of the community, public awareness, and engagement are vital in shaping the responsible use of these technologies in public spaces. Researchers should uphold ethical standards in their work, respecting the rights of study participants and ensuring informed consent.

As we look to the future, continuous innovation and investment in research will allow pedestrian and vehicle re-identification systems to adapt to emerging challenges and opportunities, ultimately contributing positively to society while safeguarding privacy, ethics, and regulatory compliance. By embracing these principles and recommendations, we can harness the potential of re-identification technology while addressing its complexities in an increasingly interconnected world.

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