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An Overview of Re-Identification

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Abstract: Pedestrian re-identification (Re-ID) is an emerging cutting-edge technology in the research area of intelligent video analysis in recent years, belonging to the category of image processing and analysis in complex video environments. This technology plays a crucial role in numerous monitoring and security applications and has been a hot topic in computer vision research. Pedestrian re-identification is considered an important sub-problem in image retrieval, which involves using computer vision algorithms to match pedestrian images or videos across devices to identify the same pedestrian from image databases of different monitoring devices. Research in this area can be traced back to the 1990s when researchers proposed various methods to address the challenge of pedestrian re-identification. This article summarizes the relevant research on personnel re-identification based on deep learning technology and its applications in different scenarios. Besides, it also identifies existing problems with this technology and its prospects.

Keywords: Re-identification; Deep learning; Image retrieval

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1. Research history

Pedestrian re-identification (Re-ID) is an emerging frontier technology in the research area of intelligent video analytics in recent years. It falls under the category of image processing and analysis in complex video environments. This technology plays a crucial role in numerous surveillance and security applications and has been highlighted in the field of computer vision. Pedestrian re-identification is recognized as a significant sub-problem within image retrieval. It involves matching pedestrian images or videos across devices using computer vision algorithms to recognize the same pedestrian from the image databases of different surveillance devices.

The research in this area dates back to the 1990s, and researchers have proposed a variety of methods to tackle the challenges in pedestrian re-identification. These methods can generally be classified into several types, including representation-based, metric-based learning, and local-feature- and global-feature-based learning. Among these methods, the representation-based learning approach extracts features from pedestrian images by mapping them to a low-dimensional space. The metric-based learning method matches different pedestrian images by calculating the distance between them. Additionally, the local-feature global-feature-based method combines local features with global features for matching. In addition, there are publicly available pedestrian re-identification datasets like Market1501, DukeMTMC-reID, and others. Evaluation metrics such as mean average precision (mAP) and cumulative matching characteristics (CMC) are also commonly employed.

In China, research on re-identification has also yielded remarkable results. Many Chinese research institutions and enterprises are actively conducting related research, including renowned institutions like Shenyang Aerospace University, Tsinghua University, and Shenyang Ligong University, as well as top companies like Huawei, Alibaba, and Baidu. These research outcomes not only propel the development of re-identification technology but also offer substantial support for the application of intelligent security and smart cities in China.

2. Current research status

2.1. Research on pedestrian re-identification theory

2.1.1. Overview of the relationship between deep learning and person re-identification

Pedestrian re-identification using deep learning techniques typically involves six steps: data preprocessing, feature extraction, loss function selection, optimization algorithm, model evaluation, and model fusion.

The first step is to gather a substantial amount of pedestrian image data, which can be acquired from publicly available datasets such as Market-1501, CUHK03, and DukeMTMC-reID. These images are preprocessed with operations such as cropping, scaling, and normalization before being input into the neural network. Next, a Convolutional neural network (CNN) is utilized as a feature extractor to obtain feature representations of pedestrians from the preprocessed images. Typically, a pre-trained CNN model (e.g., VGG, ResNet, etc.) is selected as the base network, and then additional fully connected layers and classifiers are added on top of it for the pedestrian re-identification task. To train the neural network, a loss function must be defined to evaluate the model's performance. The commonly used loss functions in pedestrian re-identification tasks are triplet loss and contrastive loss. Triplet loss calculates the loss by comparing the distance between positive samples (two images of the same person captured from two different perspectives) and negative samples (two images of different people from two different viewpoints). Contrastive loss, on the other hand, calculates loss by maximizing the distance between positive samples and minimizing the distance between negative samples. To optimize the parameters of the neural network, researchers need to select a suitable optimization algorithm. Common optimization algorithms include Adam, Stochastic Gradient Descent (SGD), and RMSProp. The model's performance needs to be evaluated periodically during the training process. To enhance pedestrian re-identification performance further, the prediction results from multiple models can be fused.

Nowadays, researchers primarily conduct in-depth studies in five main aspects: network architecture, multi-modal, cross-domain, metric learning, and video.

2.1.2. Network architecture

In 2017, Su [1] *et al.* proposed a deep convolutional model aimed at addressing the issues of misalignment and pose changes in pedestrian images. The core idea of this model is to enhance the discriminative feature representation by utilizing pose information. Specifically, the model first estimates the pose of the input image, and then segments and extracts features from the image based on the pose information. Next, a deep convolutional neural network is used to learn the extracted features, and the corresponding loss function is used for optimization. Finally, the re-identification of characters is achieved by comparing the features of different poses. In addition, the model also adopts data augmentation techniques to increase the training dataset and improve the model's generalization ability. The experimental results show that the model performs well on various public datasets.

In 2018, He [2] *et al.* proposed a method to address the issue of partial occlusion by reconstructing the spatial features of pedestrians without aligning the images. The fundamental concept is to utilize deep neural networks to learn the feature representation of pedestrians and address the issue of partial occlusion through spatial feature reconstruction. This method can more effectively capture pedestrian features and adapt to various occlusion situations, thereby enhancing the accuracy of pedestrian re-identification.

In 2021, Li [3] *et al.* proposed a method that relies on local feature association and a global attention mechanism. The fundamental concept of this method is to use local feature associations to capture the detailed features of pedestrians, while also employing a global attention mechanism to focus on the key regions in the image. This method can better adapt to various changes in pedestrians and enhance recognition accuracy.

In 2022, Xu [4] *et al.* proposed a pedestrian re-identification method based on diverse local attention networks. The fundamental concept of the method is to use local attention networks to concentrate on various regions of pedestrians in an image and allocate different weights to these regions based on their significance. This diverse local attention mechanism helps capture the detailed features of pedestrians to better handle changes in pose, illumination, and occlusion.

2.1.3. Multi-modal

In 2019, Wang [5] *et al.* proposed an innovative cross-modal pedestrian re-identification method aimed at addressing the feature differences between red, green, and blue (RGB) and infrared images. The method comprises two main components: pixel and feature alignment. The pixel alignment module reduces the modal differences at the pixel level by creating a virtual infrared image that corresponds to the real RGB image. The module utilizes the CycleGAN network, which incorporates two loss functions: cyclic loss and ID loss. The cyclical loss enables the preservation of the original multi-structure and content in the generated image, while the identity loss ensures that the identity information from the original image is preserved as much as possible in the generated image. The feature alignment module addresses the inter-modal differences caused by pose, viewpoint, and illumination. This module facilitates improved matching and comparison of features from different modalities by aligning and fusing features at the feature level. This method significantly outperforms other leading methods on the most challenging nighttime pedestrian dataset.

In 2020, Zheng [6] *et al.* proposed a new cross-modal pedestrian re-identification method. The method involves inputting RGB and depth images into two separate feature extraction networks, each generating its feature representation. Then, the features of these two modalities are combined using a novel locally heterogeneous cooperative two-way network structure. The network structure comprises two parallel sub-networks, each comprising a series of convolutional and fully connected layers. During training, the method utilizes a new loss function that incorporates a classification loss, a contrast loss, and a ternary loss. Together, these loss functions enable the network to learn more robust and accurate feature representations.

In 2022, Hafner [7] *et al.* proposed a refinement method for cross-modal pedestrian re-identification, with the aim of addressing the feature inconsistency problem between cross-modal data. First, the method takes RGB and depth images as inputs and feeds them into two separate feature extraction networks to obtain their respective feature representations. Next, a new cross-modal refinement strategy is used, in which the feature representation of one modality serves as the teacher network and the feature representation of the other modality serves as the student network. The student network is trained to learn a feature representation that closely resembles that of the teacher network by minimizing the mutual information loss between the two networks. In addition, the method incorporates an attention mechanism to highlight the information in the critical pedestrian region and enhance the robustness of the features.

2.1.4. Cross-domain

In 2019, Liu [8] *et al.* proposed a cross-domain application method called pedestrian re-identification adaptive transmission network (ATNet). This method adopts a "decomposition and integration" strategy to address complex cross-domain transmission challenges. ATNet consists of a Multi-Factor Generative Adversarial Network (GAN), a SetGAN, and a selection network. Each factor GAN focuses on achieving fine-grained and precise style transfer, while the integrated GAN can adaptively combine various factor GANs to achieve effective domain transfer. In addition, factor GAN and SetGAN are jointly optimized through end-to-end approaches. The selection network evaluates the extent to which various factors impact the transfer of different images to the target domain.

In 2022, Wu [9] *et al.* proposed a pedestrian re-identification algorithm tailored for cross-domain applications. The algorithm adopts the structure of a feature pyramid network, which is composed of a feature extraction network and a feature pyramid network. The feature extraction network is utilized to extract features from the input image, while the feature pyramid network is used to construct a multi-scale feature representation. This framework captures information at various scales and is better suited for the task of pedestrian re-identification in cross-domain scenarios. The algorithm also utilizes a knowledge distillation technique that can transfer semantic information from large-scale pre-trained models to smaller models. By utilizing a large-scale pre-trained model as a teacher model, the smaller model can acquire valuable feature representations and classification information, thereby enhancing its performance in cross-domain scenarios.

In 2023, Li [10] *et al.* proposed an innovative domain-adaptive pedestrian re-identification algorithm based on federated networks, in order to address the issue of pedestrian re-identification in cross-domain scenarios. The main concept of this algorithm is to use the joint network to simultaneously learn the feature representation and category information of pedestrians, and to address variations between different scenarios through domain adaptation techniques. This algorithm can capture pedestrian features more effectively and adapt to changes in various scenes, thereby enhancing the accuracy of pedestrian re-identification in cross-domain scenarios. Yan [11] *et al.* proposed a cross-view pedestrian re-identification method based on joint dictionary pair learning. The algorithm first learns the feature representation of pedestrians from the training data and then utilizes dictionary pair learning to match pedestrian images from different viewpoints. In this manner, the algorithm can effectively process pedestrian images from various perspectives and achieve precise pedestrian re-identification.

2.1.5. Metric learning

In 2023, Huang [12] *et al.* explored the three core components of pedestrian re-identification: feature extraction, metric learning, and deep learning. In the feature extraction stage, researchers used handmade feature descriptors such as SIFT, SURF, and HOG to capture local and global information in the image. In the metric learning stage, traditional machine learning algorithms such as K-nearest neighbors, support vector machines, and neural networks are used to understand the metric space and align pedestrian images with different perspectives, lighting, and postures into a unified space. With the continuous progress of deep learning technology, this article further elaborates on how to utilize deep learning for pedestrian re-identification tasks. Common deep learning models include CNN, autoencoder, and GANs.

2.1.6. Video

In 2017, Xu [13] *et al.* proposed jointly attentive spatial-temporal pooling networks (ASTPN) for video-based person re-identification. ASTPN can utilize the interdependencies between the input videos to compute the respective feature representations. The spatial pooling layer is used to select important regions from each video frame, while the time-domain attentional pooling can select frames containing discriminative information throughout the video sequence. Both pooling layers are guided by the distance matching information (i.e., by the loss function of the twin network performing the verification task). ASTPN conducted experiments on three datasets, iLIDS-VID, PRID-2011, and MARS, and the results show that ASTPN exceeds the performance of the state-of-the-art algorithm. ASTPN analyzed the use of spatial and time-domain pooling individually or jointly and the results show that both spatial and time-domain pooling can enhance the performance of re-identification, while the joint use of spatial and time-domain pooling can further enhance the performance.

In 2023, Liu [14] *et al.* proposed a method for re-identifying dressed pedestrians using sketch images. The technique utilizes Generative Adversarial Networks (GANs) to create lifelike dressed pedestrian images and uses a deep learning model to extract feature representations of pedestrians. By continuously adjusting the parameters of the generator and discriminator, high-quality dressed pedestrian images were finally obtained, which were then used for pedestrian re-identification.

2.2. Applied research on pedestrian re-identification

2.2.1. Overview of applied research on pedestrian re-identification

Pedestrian re-identification is primarily utilized in various fields such as security monitoring, intelligent transportation, business analysis, social media, virtual reality, and augmented reality. The main practical applications of this technology include cross-camera pedestrian tracking to enhance case detection efficiency, coordinated interaction between self-driving cars and pedestrians, customer preference analysis based on walking patterns and dwell time, automatic picture classification and label generation, personalized service recommendations based on user recognition, and improved immersive user experience for more realistic interactions.

2.2.2. Authentication

Face recognition, fingerprint recognition, iris recognition, and other methods are commonly used in identity verification to confirm the identity of individuals by extracting and comparing their features. As early as 2002, Wang Yunhong [15] *et al*. published an iris recognition-based identity identification system, which consists of four main components: iris image capture, image preprocessing, feature extraction, and feature matching. In 2023, Somers [16] *et al.* proposed an occluded person re-identification method based on body part-based representation learning. The method first uses a pre-trained CNN model to extract features for each body part and then uses a self-attentive mechanism to learn the feature representation for each part. In this way, the method can better capture local features of occluded pedestrians and reduce the effect of occlusion on pedestrian re-recognition. The method also uses the ternary loss function to optimize the network parameters, so that the representation of different body parts of the same pedestrian is closer and the representation of different pedestrian body parts is more separated. In this way, the method can improve the accuracy of occluded pedestrian identification.

2.2.3. Intelligent security

Pedestrian re-identification is a crucial area of research in intelligent security, focused on recognizing and retrieving pedestrians across different cameras. In 2020, Wu [17] proposed a method called Camera Conditional Stable Feature Generation (CCSFG), which is the first technique to synthesize cross-camera feature samples and achieve joint learning between the image encoder and feature generator. Through theoretical analysis and experimental results, we have demonstrated the effectiveness of CCSFG. This method can be used to authorize face monitoring.

2.2.4. Smart business

In 2021, You [18] *et al.* proposed a user profiling technology based on behavior perception, which was detailed in terms of user behavior data collection, processing, analysis, and application. A method based on time series was proposed for collecting user behavior data. A feature extraction method using machine learning was adopted for data processing. For data analysis, a classification algorithm based on a decision tree was proposed and finally applied to the recommendation system.

In 2023, Xue [19] *et al.* proposed a method for the automatic monitoring of library users' behavior. This method utilizes face recognition technology to automatically monitor and record library users' entry and exit, as well as their reading behavior, to achieve intelligent management. At the same time, when combined with other data sources, it can also analyze users' reading preferences and behavioral habits to enhance the quality and efficiency of library services.

2.2.5. Human-computer interaction

In 2022, Li [20] proposed a design for a home service robot that utilizes SLAM navigation and face recognition. The face recognition function was integrated into the interaction between the home service robot and humans, encompassing tactile manipulation, gesture manipulation, and voice manipulation.

3. Review of the study

3.1. Summary of the current situation and issues

Nowadays, re-identification technology has reached a high level of accuracy and robustness in terms of technological advancement. Through the use of deep learning, neural networks, and other algorithms, re-identification technology can extract features from images, videos, and other data, and perform comparison and matching. Meanwhile, as the data set continues to expand and the algorithm undergoes continuous optimization, the performance of re-identification technology is constantly improving. Re-identification technology has been applied in various research areas, including identity verification, image retrieval, video surveillance, and medical diagnosis. Meanwhile, with the continuous development of technology and the expanding application scenarios, the prospects for re-identification will be even broader.

Despite the widespread application of this technology, it still comes with several challenges. High-quality data from various sources in different formats is needed for data collection and processing. The channels of data acquisition are often constrained by hardware limitations, and many theoretical studies rely on existing image libraries, which are not yet fully applicable in practical scenarios. To accommodate more diverse data acquisition in the future, data processing methods need to evolve to meet the changing demands. In terms of robustness and generalization ability, there is still a need to enhance performance in diverse and complex environments, such as lighting changes, occlusion, and posture variations. This improvement can be achieved by integrating AI to enhance character recognition accuracy. Besides, ensuring privacy and security are also essential to prevent data leakage and misuse, and to ensure that all procedures performed are legal. Enhancing computing efficiency and reducing costs are also major concerns in the realm of computing resources and performance, requiring further technological advancements. Lastly, customizability is also a crucial aspect in the development of re-identification technology to ensure that the needs of the users are met.

3.2. Prospects

The performance of state-of-the-art models on certain benchmark datasets is approaching saturation, but their capacity to generalize to real-world applications still requires improvement. Future research on Re-ID is likely to focus on the following areas:

(1) Large-scale spatiotemporal pedestrian re-identification

With the proliferation of surveillance devices and technological advancements, there is an increasing collection of pedestrian images and video data. The utilization of large-scale spatio-temporal data to enhance the performance of Re-ID is currently a key focus of research.

(2) Unsupervised pedestrian re-identification

Compared with the traditional methods, the unsupervised learning method only needs unlabeled data instead of a large number of labeled data. This presents significant potential for the practical implementation of re-identification, as it is extremely challenging to acquire a substantial amount of labeled data in real life.

(3) Dress-changing pedestrian re-identification

The advancement of clothing transformation technology has led to the emergence of dress-changing pedestrian re-identification. The research holds significant importance for an intelligent society. However, the current research in this field is still in its early stages.

(4) Cross-modal pedestrian re-identification

With the widespread use of various sensors and data acquisition devices, pedestrian images and video data exhibit diverse modal characteristics, including RGB images, depth images, infrared images, and more. How to effectively utilize cross-modal data to enhance the performance of Re-ID is currently a key focus of research.

(5) Fine-grained identification for pedestrian re-identification

In certain application scenarios, such as face recognition and pedestrian tracking, a more detailed recognition of pedestrians is necessary. For instance, the system needs to differentiate between various facial expressions, poses, or appearances of the same individual under different lighting conditions. Therefore, improving the re-identification model's ability in fine-grained recognition is also an important concern.

(6) Robustness of pedestrian re-identification

The images and videos of pedestrians may be affected by various factors, such as occlusion, changes in illumination, and background interference. Therefore, it is essential to improve the robustness of the re-identification model in these challenging scenarios as an important research focus.

(7) Privacy protection for pedestrian re-identification

Given that re-identification technology involves the identity information of pedestrians, it is essential to fully consider privacy protection while ensuring the performance of the system.

(8) Evaluation metrics and benchmark datasets for pedestrian re-identification

To objectively assess the performance of re-identification models, a set of well-established evaluation metrics and benchmark datasets are required. Several existing re-ID datasets, such as Market1501 and DukeMTMC-reID still have limitations in terms of sample imbalance and perspective differences. Therefore, it is important to explore how to construct more comprehensive and reasonable re-identification datasets.

3.3. Perspectives and expectations

There are various perspectives and expectations for the future of re-identification technology.

(1) Enhancing accuracy and robustness

Current re-identification methods still require improvement in accuracy and robustness, especially in complex scenarios. For instance, recognition performance may be affected in situations such as changes in lighting, occlusion, and the target object wearing different clothing. Therefore, future research should focus on utilizing advanced techniques, such as deep learning and transfer learning, to enhance the model's recognition ability in diverse scenarios. By training more powerful models, we can attain greater accuracy and robustness in re-identification.

(2) Cross-modal and cross-view recognition

Existing re-identification methods primarily rely on uni-modal data (e.g., RGB images) for recognition. However, data in the real world is diverse, encompassing infrared images, depth images, and more. In addition, the target object may be observed from different viewpoints, such as the front, side, and back. Therefore, future research should focus on achieving cross-modal (e.g., RGB, infrared, depth, etc.) and cross-view (e.g., front, side, back, etc.) recognition for a broader range of application scenarios. This will help improve the practicality and universality of re-identification technology.

(3) Real-time and efficiency

As surveillance systems continue to grow in scale, real-time performance and efficiency have become important challenges for re-identification technology. For instance, real-time surveillance and rapid identification are essential in the realms of public safety and traffic management. Therefore, future research should focus on optimizing the algorithms and enhancing the running speed of the models to meet the demands of real-time surveillance. By reducing computational complexity and optimizing hardware devices, we can achieve more efficient re-identification techniques.

(4) Privacy protection

The use of re-identification technology in security monitoring and other fields may raise concerns about personal privacy. For instance, analyzing surveillance videos in public places may lead to the leakage of sensitive information, such as personal whereabouts and trajectories. Therefore, future research should focus on how to protect the privacy rights of the identified subjects while maintaining recognition performance. This may require the use of privacy-preserving techniques, such as differential privacy, homomorphic encryption, etc., to ensure the security of personal information.

(5) Multi-source data fusion

Existing re-identification methods primarily rely on single-source data for identification. However, real-world data is diverse, encompassing video, images, text, and various other types. Therefore, future research should focus on realizing the fusion of multi-source data to enhance the accuracy and robustness of recognition. By combining various types of data, a more comprehensive and accurate re-identification model can be created.

(6) Adaptive learning and online updating

To adapt to changing scenes and target objects, future re-identification technology should be capable of adaptive learning and online updating. This will enable the adjustment of model parameters in real time, thereby enhancing recognition performance. For instance, when a new surveillance camera is deployed or the target object's dressing style changes, the system should be capable of learning and adapting to these changes automatically. By implementing online learning algorithms and incremental learning techniques, we can achieve a more adaptable and intelligent re-identification system.

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