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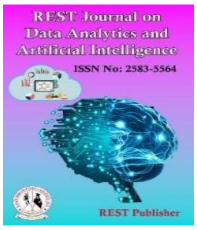

Identification of Changing Personnel with Double-Layer Network Fusion and Bi-Level Monitoring Mechanism

[*]S. Gomathi Meena, S. Dharani, R. Manikandan, Sam. V. Jeshrak
PERI College of Arts and Science, Chennai, Tamil Nadu, India.
[*]Corresponding Author Email: s.gomathimeena@gmail.com

Abstract*: Person re-identification (Re-ID) is an essential part of visual surveillance that aims to identify and locate persons from multiple network cameras without conflicting viewpoints. Although significant advances have been made in recent years with the use of deep learning, there are still many challenges in vision such as occlusion, exposure, background clutter, misalignment, scale, perspective, low resolution and illumination, and cross-camera methods. Dressing redefinition is a hot topic in education right now. Most existing methods assume that people's clothes do not change in a short time, but they do not apply when people change clothes. Accordingly, this article introduces a double-layer garment changer re-identification network that integrates the secondary care process through clustering and fine-grained knowledge in space and training the garment classification branch to increase the sensitivity of the network to garment characteristics. In this method, auxiliary equipment such as human bone is not used and the complexity of the model is greatly reduced compared to other methods. This article runs experiments on the famous redefined PRCC data and large-scale long-term dataset (LaST). Experimental results show that the method in this article is superior to existing methods.*
Keywords: *Channels, Clothes Features, Clothes-Changing Complexity, Dual-Branch Network, Fine-Grained Person Semantic Information, Spaces, Two-Level tention Mechanism.*

1. INTRODUCTION

In recent years, person identification has attracted attention due to its wide application in various fields such as intelligent video surveillance [1], robotics [2], and human-participant interaction [3]. In particular, airports, banks, military bases, parks, roads, schools, etc. for public safety and security in smart places. It is one of the main tools of visual surveillance that can identify and track individuals in videos (or photos) from multiple non-overlapping cameras installed in public places. It is absolutely impossible to rely on human intervention to identify people of interest from the huge amount of Video data collected every day, so visual scientists have proposed various methods to solve this very difficult problem. Methodologically, person re-identification means identifying and monitoring people through a network of non-overlapping cameras installed indoors and outdoors. Given a picture of a person taken by one camera, the re-identifier's job is to identify that person from a pre-recorded location taken Although there are differences between the publications appearing in the top ranks, complementing the accuracy of the existing measurement data, the problem is still far from being resolved and translated. This can be attribut ed to a number of challenges (blockages, changes in people's thinking, changes in thinking for example, we provide an in-depth analysis of the impact of the most popular Re-ID challenges by discussing the performance of each challenge in the most popular computer forums and magazines. This provides insight into the complexity of each challenge throughout the Re-ID process. Also, according to the progress of the review, best practices achieving state of the art (SOTA) in each competition are clearly and rigorously analysed/ Additionally, we seek to set future directions for researchers by reviewing publications on each challenge and discussing the limitations and benefits of the intervention. Reflect the difference between close range and real-world use. Finally, we present the analysis with some suggestions that we hope will contribute to better research and studies in this area, as well as presenting the topics and showing interesting methods. For readers in either of these situations, this survey also provides detailed information on how these challenges have been resolved in the past and how various aspects of deep learning (DL) have been used to improve individuals' Re-Identity, taking into account the impact of each challenge. The results of this article can be summarized as follows. First, the article uses IBN-Net as its backbone. It uses a sample normalization (IN) layer to remove individual differences and a batch normalization (BN) layer to extract features such as individual textures and silhouettes. Uses a two-level view module to capture and aggregate more detailed features across sites and channels. Experiments show that this two-level monitoring enables the network to learn global and local features. This is necessary for redefining the change of clothing Second, to suit the redefinition of garment changers, this article adds a branch of garment classification to constrain the model's view of garment properties. Third, this article conducts extensive experiments on the most frequently used data and large inter temporal data. All with good results.

2. LITERATURE SURVEY

Person redefinition was first recognized as a single task in computer vision at the 2016 CVPR conference. Its mission to redefine the clothes-changing (long-term) traveller is a first in 2019. However, little research has been done on redefining clothing alterations. The results with the development of deep learning, current studies are based on neural networks to learn the characteristics of discrimination (Gong et al., 2021; He et al., 2021; Li et al., 2018; Xu et al., 2018).

2.1 Non-Clothes-Changing Person Re-Identification: For example, in [10–12] proposed a strategy to eliminate bias by bias. It balances the weight of colour features and non-colour features in the neural network by discarding some of the colour information in the training data. Thus, the effect of colour segmentation is overcome. She is waiting for someone (2021) Use Transformer to redefine and first recommend the use of the Jigsaw patch module (JPM) to create powerful features with greater separation and greater scope.re not good. It also optimizes feature representation, which can resolve misalignment of input images [13] added exposure-guided partial maintenance (PPA) and auditory feature composition (AFC) to the network. Their purpose is to use pose data to examine solid and non-rigid concepts. Then use global properties and partial properties as final property placement. However, this study focuses on short-term redefinition as beautiful colors. These don't work very well when people change clothes.

2.2 Redefining the changer: There is little research on redefining the changer that distinguishes people based on characteristics unrelated to clothing, such as body size, face, or 3-D shape and focused on facial data analysis and facial feature removal to improve model accuracy [14]. Remove tissue-insensitive 3D image embedding directly from 2D images by adding 3D body reconstruction as an adjunct. However, most of these methods use auxiliary equipment such as human bones. It also complicates the build. In this paper, a mesh unaffected by RGB images is introduced to learn by tracing the characteristics of the model. It also uses the apparel distribution branch to limit the apparel specifications published by the network. System can compete with existing systems.

3. IBN-NET FRAMEWORK

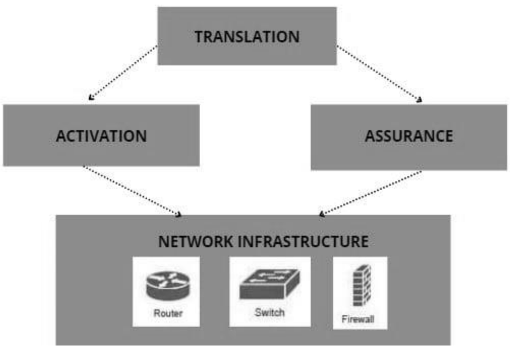

FIGURE 1. Frame Work of IBM-Net

Figure 1 shows the framework of the method. Backbone uses IBN-Net, removing the previous two layers. It also adds a secondary monitor and a second channel monitor module. Both are connected in series. Finally, it uses a multi-layered perceptron (MLP) to classify the extracted features. In addition to character classification, split-leg outfits have been added to make the model suitable for changing outfits. In this paper, a two-level view module is used to capture the semantic information of characters, suppress the effect of background information, and extract the finer grained features of the characters. The content will be covered in the two-level view module. In addition to the individual branch, this paper also adds a clothing branch. The clash of shocks is achieved by dividing the clothes. In the process of reducing the resistance loss, the model is forced to learn non-wear characteristics.

3.1. Reset 50: Most of the popular network models now use Resnet-50 as the backbone. BN in the network can make all models have different content for each model. This is great for distinguishing between different models. However, in the Clothes Changer review, the appearance of similar models has changed significantly. Using BN layers has the disadvantage of verifying the accuracy of the network. In addition, due to the change in the angle of view of the camera, there may be defects such as blurring, congestion, posture, color, style and brightness of the images taken of the people. People's appearances change frequently, especially in the changing scene. To address these issues, this article uses IBN-Net [15] as the backbone. It combines the IN layer and the BN layer in the network to fulfill the limitations of both. Layers contain images that do not change due to changes in appearance (for example, style, color, and brightness). BN layer properties include texture and stroke.

4. THE TWO-STAGE IMAGING MODULE

Aims to redefine the person who will change their clothes in order to extract the characteristics of the person. However, background information is often captured along with human images. This includes a redefinition task. In the re-identification of disguises, the feature of the attire is no longer used to distinguish people; therefore, less jobs are available. Tracking mechanisms have proven effective for extracting important information from images. However, in the known behaviour of changing clothes, it is necessary to capture beautiful features in limited situations due to the failure of clothing features. Capturing more fine-grained character traits is the goal of solving the problem of redefining clothing alterations. To solve this problem, this document uses a two-level view module to guide the network to extract properties from different images. Additionally, it uses coarse-grained and fine-grained features for further learning. SAM works using two pools. The first market pool is the average pool function that calculates the average cost of all features in the channel. The second pooling operation is the max pooling operation, which calculates the maximum value of each channel. These two common maps are combined and fed into a convolutional process with a filter size of 7x7, resulting in a 2D spatial view map. The main advantage of using the spatial colour module is the ability to choose to highlight important features and limit interference. This allows CNN to focus on the most informative part of the input image, resulting in better performance. Additionally, the spatial listening module is calculated because it uses only two streams and one convolutional layer. Another advantage of using the SAM is its interpretation. The attention map generated by SAM shows the most important parts of the input image and allows us to understand which part of the image CNN is paying attention to for the task at hand. The spatial attention module is a spatial observation module in convolutional neural networks that selectively amplifies the maximum information of an input image. SAM uses the relationship between features to calculate the interaction map, which is easy to calculate and interpret. Spatial view modules have been implemented for various computer vision tasks, including object detection, semantic segmentation, and image tagging. Seesaw Loss is a negative function that addresses the limitations of cross entropy loss for long tail segmentation. This goal is to reduce heavy penalties for competing groups while compensating for the negative risk from mitigation. Seesaw Loss dynamically adjusts the distribution of classes between head and tail so that the optimization does not affect the main classes. The compensation system encourages the model to learn the unique features for each class and reduce the cost of false positives and negatives. Lost Seesaw offers a solution to the sample partitioning problem and can improve the prediction accuracy of long-tail data. The plan can be expanded to cover many machine learning applications and has real-life implications.

Metrix is a new technology that brings many benefits to deep learning. It provides a way to create a variety of teaching examples that can lead to a more accurate and powerful model, allowing for the representation and impact of the text. The method is easy to use and can be used in many types of unemployment, making it a versatile tool in deep learning. As the use of deep learning continues to increase, techniques like Metrix will become increasingly important for improving accuracy and reducing competition. Using Metrix, we can create more powerful and reliable models that capture the underlying data. Supervised contactless less Discrepancy tracking is a powerful technique in machine learning that can help better analyze, group, and classify data. It is based on the idea of bringing similar contents together while storing different information on different contents. It has important features suitable for monitoring learning and has many applications in various machine learning. Unsupervised feature loss the main advantage of using UFLoss is that it can help improve the accuracy of DL models. UFLoss is used to train deep learning models to detect features not found in small patches, allowing the model to adapt to new data. Using UFLoss, deep learning models can capture central patterns and key points important to many applications such as image recognition, image segmentation, and object detection. These resources can facilitate deep learning models to recognize, classify and characterize objects in images. Plou Loss PIoU loss is the loss obtained from the IoU metric to detect object orientation in images or videos. Knowing the right objects is helpful in scenes where orientation plays an important role. Using PIoU Loss can reduce false positives and false positives, thereby increasing the accuracy of object detection algorithms. With the continuous improvement of target detection algorithms, we hope to see more versions of PIoU Loss that can be adapted to different applications and situations. Triplet loss function Triple Entropy Loss is a powerful training method that combines the advantages of Cross Entropy Loss and Triple Loss to achieve optimum correlation in neural networks. Although TEL is computationally more expensive than some training programs, its benefits include overall improvement and elimination of the need for pre-training. Triple entropy loss has applications in many areas, including face recognition, image retrieval, and natural language processing.

5. EXPERIMENT

Dataset In this paper, the effectiveness of the proposed method was validated on a garment change reanalysis of PRCC and LaST data. PRCC is a public database for personal identification used in 2020. It has 221 people and three camera views [16]. Images in the PRCC dataset include many variables such as clothing, lighting, occlusion, pose, and appearance. Each camera image contains 50 photos per person. There are approximately 152 images of each person in the database (33,698 images in total). Last is a large-scale spatio-temporal redefinition of data published in 2021. Contains 10,862 travelers and over 228,156 images (Shu et al., 2021). Compared to the available data, LaST is more complex and diverse. Including people from different times (day to night), different cities and different countries, from children to 70-year-olds. Seventy-six percent changed clothes. Evaluation Index This document evaluates the Re-ID accuracy of the method of two datasets with Competitive Accuracy (CMC) and Average Average Precision (mAP). CMC uses Rank-n to represent the accuracy of ReID. This calculation method is for calculating the correct value of individual questions in results above n. The final Rank-n value is the average of the Rank-n of all test data. The average precision map score sums and averages the average accuracy of the tasks and shows the overall accuracy of the Re-ID.

FIGURE 2 &3. PRCC Data Visulations result

Test details Test platform's operating system is Ubuntu16.04. It uses two NVIDIA 2080TI GPUs, each with 12GB of video memory. The entire network is built in the PyTorch framework. batch size is set to 32. There are eight people in a group. Each person has four pictures. The input image is resized to 384 × 192. Random horizontal flip, random cropping, and random deletion are used for data enlargement. In this paper, a spatial secondary view module and a second channel view module have been added after the second residual block and fourth residual portion of the model. It sets both in one connection. In this text, the number of divisions of the spatial color n is set to 4. The number of listening channels is 2. The model was trained 60 times with the Adam optimizer suggested by [17]. Work started at 3. 5e-4 is divided by 10 every 20 times. Visual Analytics Uses heat images to show the color of different models of areas of interest to better see how the method works in practice. As shown in Figure

2, the first column is the first-person image, the second column is the heat map visualized using IBN-Net, and the third column is the plan in this article. From Figure 3 we can see that our model places more emphasis on the body region than on the sole. also attracted wider attention. Special reports tend to focus on shoulders, body shape, body and body features that are not related to clothing. Therefore, the method in this article is suitable for redefining an exchange agent.

6. CONCLUSION

This article introduces a two-level monitoring module and a dual process model for redefining the wearer of changing clothes. It uses the previous work, IBN-Net, as the backbone and adds both spatial and channel monitoring in the network. It then uses the person and garment classification binary branch to extract the garment features. This method does not use other methods. Also, the model is heavier. The mesh model captures the characteristics of people changing clothes. Better results can make my clothes look bad from my photos and cope with the redefinition of people changing clothes. The superiority and robustness of the proposed method is verified by testing two popular traveler Re-ID datasets and comparing them with the current popular method. The article also proves the effectiveness of the proposed two-stage tracking module and dual task with experiment. The method proposed in this document can be used for smart surveillance, especially tracking criminals (who try to avoid detection by changing clothes) and missing persons.

REFERENCES

[1]. Y. Wang et al.A real-time and unsupervised face re-identification system for human-robot interaction Pattern Recognit. Lett. (2019)

[2]. Z. Ming et al.Deep learning-based person re-identification methods: a survey and outlook of recent works Image Vis. Comput. (2022)

[3]. D. Wu et al.Deep learning-based methods for person re-identification: a comprehensive review Neurocomputing (2019)

[4]. R. Quispe et al.Improved person re-identification based on saliency and semantic parsing with deep neural network models Image Vis. Comput.(2019)

[5]. Y. Chen et al.Deep and low-level feature based attribute learning for person re-identificationImage Vis. Comput.(2018)C. Su et al.

[6]. Multi-type attributes driven multi-camera person re-identification Pattern Recognit.(2018)I.B. Barbosa et al.Looking beyond appearances: synthetic training data for deep CNNs in re-identification

[7]. Comput. Vision Image Understanding (2018)

[8]. Z. Li et al.Person re-identification with part prediction alignment Comput. Vision Image Understanding (2021)

[9]. X. Hu et al.Hypergraph video pedestrian re-identification based on posture structure relationship and action constraintsPattern Recognit. (2021)

[10]. T.T.T. Pham et al.Fully-automated person re-identification in multi-camera surveillance system with a robust kernel descriptor and effective shadow removal method Image Vis. Comput.(2017)

[11]. Gong, Y., Huang, L., & Chen, L. (2021). Eliminate deviation with deviation for data augmentation and a general multi-modal data learning method. In Computer Vision and Pattern Recognition (pp. 1–12). Academic Press.

[12]. He, S., Luo, H., Wang, P., Wang, F., Li, H., & Jiang, W. (2021). Transreid: Transformer-based object reidentification. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 15013–15022). IEEE.

[13]. Li, W., Zhu, X., & Gong, S. (2018). Harmonious attention network for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2285–2294). IEEE

[14]. Xu, J., Zhao, R., Zhu, F., Wang, H., & Ouyang, W. (2018). Attention-aware compositional network for person re-identification. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp.2119–2128). IEEE.

[15]. Chen, J., Jiang, X., Wang, F., Zhang, J., Zheng, F., Sun, X., & Zheng, W. S. (2021). Learning 3D shape feature for texture-insensitive person re-identification. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 8146–8155).

[16]. Pan, X., Luo, P., Shi, J., & Tang, X. (2018). Two at once: Enhancing learning and generalization capacities via ibn-net. In Proceedings of the European Conference on Computer Vision (pp. 464–479).

[17]. Yang, Q., Wu, A., & Zheng, W. S. (2019). Person re-identification by contour sketch under moderate clothing change. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(6), 2029–2046.

[18]. Kingma, D., & Ba, J. (2014). Adam: A method for stochastic optimization. Computer Science.