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Person Re-Identification

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A B S T R A C T

Deep learning is a branch of ML (Machine Learning). It is completely based on artificial neural networks. Deep learning is useful in our daily lives because it can process large volumes of data volumes and is powerful in handling huge datasets of unstructured data. Deep learning plays a major role in image and video processing or computer vision applications. It is generally used to classify images based on their similarities and also in object recognition in videos. In this study, the discussion is all about the Person Re-Identification. The Person Re-Id is that the problem of matching people across disjoint camera views in a multi-camera system. It is useful for a number of public security applications such as intelligent camera surveillance systems. The goal of Re-Id is to identify a person in a network of non-overlapping cameras, which means to match the images of the same person across various cameras or a single camera across different time spans. This task seemed to be a very difficult thing because there may be a significant change in human pose and shape across time changes. Moreover, there are a huge number of drawbacks in person reidentification like time variation in case of moving objects, etc. The drawbacks in the spite of person reidentification are decreased by implementing new algorithms all the time in rapid growth of machine learning. The various studies demonstrate that the accuracy of person reidentification (Re-Id) can be improvised by implementing effective algorithms that can easily identify a person in a huge dataset. This study includes some of the algorithms like Market-1501, DukeMTMC-reID, CUHK03 which helps to discuss this study effectively. As a result of this study, a detailed comparison is done on the various algorithms and showcased.

Keywords: Machine Learning, Artificial Neural Networks, Image & Video processing, Object Recognition, Unstructured data.

1. Introduction

Person re-identification is defined as the process of identifying pedestrian images in disjoint or non-overlapping cameras at different time intervals . The images found in different time intervals should match with one another. A good re-ID technique should have three phases: (1) detecting a person, (2) tracking a person, (3) retrieving the person . The person re-ID technique is still a challenging dream for the researchers. The cameras click different images of a person in an uncontrolled environment. The images may also be of low quality, unidentifiable, etc. It may become difficult for the model to detect the person. So, in order to get more accurate results, new features are used like identifying the person based on his dress colors or any object he is carrying. However, the appearance features may also fail like similar color dresses and objects. So, the re-ID technique is still being improvised by implementing best algorithms in which new features are added for further accuracy. Mainly, this person re-ID technique came into consideration with the urgent demand for public safety and an increasing number of surveillance cameras.

2. Literature Review

- This paper propose that how person re-identification technique is useful in identifying a person by non-linear deep feature mapping. Similar samples are mapped close to each other and dissimilar samples are kept far apart. Deep metric learning goal is to learn mapping from the input to low dimensional embedding space. here, the network is trained by tuning the datasets on person re-ID datasets, a sample is taken randomly and is matched with a mini set of images by traversing sequentially. [1]
- To solve all the problems regarding re-ID, the paper proposes to learn feature representation and distance metric jointly in end-to-end manner using hardness aware structural metric learning. By the proposed approach, we can learn more discriminant deep features that are used in person re-ID for variation in person appearance. [1]
- This paper propose that Beyond Pairwise Matching with High-Order Relevance Learning method for unsupervised Re-ID is proposed. The multi hypergraph structure employed to model the relationship between the probe and the gallery data in the person reidentification task. The learning on multi hypergraph is conducted to estimate the relevance from each probe and the existing persons in gallery. It is not limited to the selected features and data and has high potential to be further applied in other tasks, and extended to discover more relationships among the data [2]
- In this study, multi-scale deep supervision with attention block deep model for person re-ID introduced. Here, the experiment shows that the proposed model exceeds the competitive model. Infrared-Visible Pre-ID is used to match a particular person across visible and thermal cameras. There are mainly three existing types of deep Pre-ID models, i.e., identification model, verification model and distance metric

learning model. In this section, we present the carefully designed deep construct by first presenting the training network, and then describing the loss functions. [3]

- The attention block adopted in this paper consists of channel attention and spatial attention. The channel attention outputs a set of weights
- for different channels while the spatial attention concentrates on the informative part. The Datasets used in this paper are Market-1501 dataset, CUHK03 dataset, Duke MTMC-re ID dataset, MSMT17 dataset. In this paper, they used Pytorch to implement the proposed model. The ResNet-50 with pre-trained parameters on ImageNet is used as the backbone network. [3]
- In this paper, it is proposed to tackle the person re-ID as a rank fusion task, which means that only predictions are made from the existing database on the collected samples. Here, three representative fusion methods are included which are mean fusion, the majority voting, the adaptive weighted fusion, average distance fusion, and Sakrapee feature-based re-ranking method. Different methods have different kinds of features. So, the strengths, weaknesses and accuracies vary. [4]
- This paper proposes an unsupervised metric learning method for person re-ID. Here, the idea is that the samples of a person are collected from different camera views. The technique in this paper is in such a way to reduce the problem of human appearance variation. The training set consists of many camera views of a person, so the identification of person gets easier even though the person is in different pose. [5]
- The main contribution of this paper is they proposed a new novel method for personal identification. This method explores relationships among person images from different cameras using unlabelled samples, The inconsistency in camera views is modelled by a shared mapping and a set of view specific mappings, They enhanced the distribution consistency among camera views in the transform subspace, so that the learned metrics are more convincing. [5]

3. Methodologies

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. This layer is the first layer that is used to extract the various features from the input images. In this layer, the mathematical operation of convolution is performed between the input image and a filter of a particular size MxM. By sliding the filter over the input image, the dot product is taken between the filter and the parts of the input image with respect to the size of the filter (MxM).

In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim this layer is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map. Depending upon method used, there are several types of Pooling operations. In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.

4. Results

PAPER	AUTHOR	METHOD	RESULT
[1]	X. Yang, P. Zhou and M. Wang	non-linear deep feature mapping.	Similar samples are mapped close to each other and dissimilar samples are kept far apart. Deep metric learning goal is to learn mapping from the input to low dimensional embedding space. Here, the network is trained by tuning the datasets on person re-ID datasets, a sample is taken randomly and is matched with a mini set of images by traversing sequentially.
[2]	Xibin Zhao, Nan Wang, Yubo Zhang, Shaoyi Du, Yue Gao	unsupervised Re-ID	The multihypergraph structure employed to model the relationship between the probe and the gallery data in the person reidentification task. The learning on multihypergraph is conducted to estimate the relevance from each probe and the existing persons in gallery. It is not limited to the selected features and data and has high potential to be further applied in other tasks, and extended to discover more relationships among the data, e.g., providing more visual appearance models.

[3]	D. Wu, C. Wang, Y. Wu, Q. -C. Wang and D. -S. Huang	multi-scale deep supervision with attention block deep model	Here, the experiment shows that the proposed model exceeds the competitive model. Infrared-Visible Pre-ID is used to match a particular person across visible and thermal cameras. There are mainly three existing types of deep Pre-ID models, i.e., identification model ,verification model and distance metric learning model.
[4]	D. Cheng, Z. Li, Y. Gong	Fusion of Multiple Person Re-id	In this paper, it is proposed to tackle the person re-ID as a rank fusion task, which means that only predictions are made from the existing database on the collected samples. Here ,three representative fusion methods are included which are mean fusion, the majority voting , the adaptive weighted fusion, average distance fusion, and Sakrapee feature-based re-ranking method . Different methods have different kinds of features. So the strengths , weaknesses and accuracies vary. The person re-ID fusion method is based on the GLAD approach. This approach is based on standard probabilistic inference on a model.
[5]	Y. Feng, Y. Yuan	Unsupervised metric learning	Here ,the idea is that the samples of a person are collected from different camera views. The technique in this paper is in such a way to reduce the problem of human appearance variation. The training set consists of many number of camera views of a person, so the identification of person gets easier even though the person is in different pose.

5. Conclusion

In this paper, we present an effective person re-ID framework by discriminatively learning a nonlinear deep feature mapping from person images to low-dimensional embeddings, where similar samples are mapped closer to each other, while dissimilar samples are pushed farther apart. The proposed approach jointly learns feature representation and distance metric in an end-to-end manner. The various studies demonstrate that the accuracy of person reidentification (Re-Id) can be improvised by implementing effective algorithms that can easily identify a person in a huge dataset . Person reidentification is aimed at solving the problem of matching and identifying people under the scene of cross cameras. So in person re-ID a person can be matched only if the person is previously found under camera surveillance or else it will be his first time to get into the re-ID.

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