



Dual Regularized KISS Metric Learning for Person Reidentification

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ABSTRACT

Person re-identification denotes to the task of matching images of walkers across different camera views at different locations, and the system is particularly popular for video investigation. But, person re-identification remains a challenging problem due to the real-world problems of background confusion, constrictions, small target size, and large intra-class variability in clarification, viewpoint, and position. To overcome this problem, it introduces regularization techniques to improve the keep it simple and straightforward (KISS) metric learning for person re-identification. It proposes dual-regularized KISS (DR-KISS) metric learning. The DR-KISS metric learning is the two covariance matrices to reduce the issue that large Eigen values in the true covariance matrix are highly biased. This regularization is necessary and the proposed method is robust for generalization. The DR-KISS, firstly the local maximal occurrence (LOMO) are extracted from each sample and then principal component analysis (PCA) is conducted to obtain a low-dimensional feature representation for each sample. Finally the DR-KISS is accomplished and the matching rank is creating according to the query target. The DR-KISS approach to achieve performance accuracy.

INTRODUCTION

In existing methods compute the distance between two images with a common metric. These methods assume that there is a common transition model or subspace for all the persons recorded in the camera network. However, this assumption does not hold in Most cases, because there are large visual appearance changes caused by variations in view angle, lighting,

and background clutter in a typical camera network. It propose dual-regularized KISS (DR-KISS) metric learning. The DR-KISS metric learning is the two covariance matrices to reduce the issue that large Eigen values in the true covariance matrix are highly biased. This regularization is necessary and the proposed method is robust for generalization. The DR-KISS, firstly the local maximal occurrence (LOMO) are extracted from each sample and then principal component analysis (PCA) is conducted to obtain a low-dimensional feature representation for each sample. Finally the DR-KISS is accomplished and the matching rank is creating according to the query target. The DR-KISS approach to achieve performance accuracy.

DESIGN

GET VIDEO FROM CAMERA

In this module used to collect the videos and splitting images. In our framework, this is addressed by different Multi distance metrics corresponding to different transition models or subspaces between different cameras, and assuming that they are different but related. The first step is collecting the video files from different camera. The video files contain the various position of the person. The second step is split the video into images.

CONVERT VIDEO INTO FRAMES

In this module used to convert the video using Daubechies' Wavelets techniques. Creating tables (indexes) that point to the location of folders, files and records. Depending on the purpose, indexing identifies the location of resources based on file names, key data fields in a database record, text

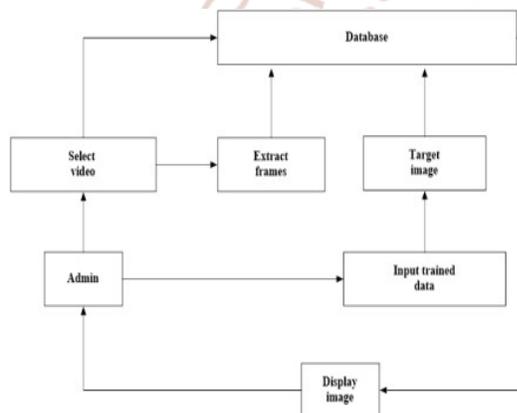
within a file or unique attributes in a graphics or video file. The query images are preprocessing and then forming a feature vector. The feature vector stored in database. This method is used to easily search the data in database.

INPUT TRAINED DATASET

In this module the admin give the input trained dataset based on the previous extracted frames. The collection of video from the App Database has to initialize in first segment. Since, the frames are located into the database the location has to be browsed by the admin. The input trained dataset have to be module into the segments classified into the initial stage of this module.

DISPLAY IMAGE

This module is introduced to load the input trained data into the segments. The Image location has to be selected from the Database. Since, the frames are extracted from the database the stages have to initialize clearly.



IMPLEMENTATION

It proposes dual-regularized KISS (DR-KISS) metric learning. The DR-KISS metric learning is the two covariance matrices to reduce the issue that large Eigen values in the true covariance matrix are highly biased. This regularization is necessary and the proposed method is robust for generalization. The DR-KISS, firstly the local maximal occurrence (LOMO) are extracted from each sample and then principal component analysis (PCA) is conducted to obtain a low-dimensional feature representation for each sample. Finally the DR-KISS is accomplished and the matching rank is creating according to the query target. The DR-KISS approach to achieve performance accuracy.

RELATED WORK

In the introduction Section, we briefly reviewed popular features used in person re-identification. In recently, training a robust and efficiency matching scheme has been received increasing attentions. Large margin nearest neighbor metric (LMNN) are proposed to improve the performance of the traditional kNN classification. However, LMNN is time-consuming for using the k closest within-class samples. By minimizing the differential relative entropy between two multivariate Gaussians under constraints on the distance function, information theoretic metric learning (ITML) [9] is built on the Mahalanobis distance metric learned from the information theoretic perspective. Zheng et al. proposed a soft discriminative scheme termed relative distance comparison (RDC) by large and small distances corresponding to wrong matches and right matches, respectively. To some extent, the solution of RDC is complicated, and it can be solved by an iterative optimization algorithm. The L2 distance, Mahalanobis Metric, and Bhattacharyya distance are also applied to person re-identification. However, they perform poorly when the view conditions change greatly. As a pairwise method, rank support vector machines (RankSVM) have been extensively used in retrieval related problems. The Ensemble RankSVM is presented by Prosser et al. to handle the scalability issue by using ensemble learning. Besides distance metric learning based matching schemes, contextual cues are very useful for improving the accuracy and robustness of person re-identification. By utilizing subspace learning, a brightness transfer function is proposed to deal with the illumination changes between different cameras. Makris et al. proposed a scheme to determine the topography of cameras by observed location and velocity of moving objects. Hamdoun et al. collected interest points from surveillance video shots to estimate the appearance model. The contextual cues can be implemented as a preprocessing step to improve the system of person re-identification.

CONCLUSION

We formulate person re-identification in a camera network as a multi-task distance metric learning problem. In particular, we propose a dual-regularized KISS (DR-KISS) metric learning for person re-identification in a camera network. In order to cope with complicated conditions in a typical camera network such as variations in illumination, camera viewing angles, and background clutter, designs

multiple different Mahalanobis distance metrics for different camera pairs, and addresses the fact that these Mahalanobis distance metrics are different but related. These Mahalanobis distance metrics are jointly learned by adding graph-based regularization to alleviate over-fitting. Our experiments validate that the performance of is substantially better than other current state-of the-art person re-identification methods. It is worth pointing out that although our proposed DR-KISS is formulated specifically for person re-identification over a camera network, it can be applied to solve other pattern recognition problems.

FUTURE ENHANCEMENT

Fortunately, there has been a lot of work on multi-task learning that may provide helpful insights. It also would be useful to build better multitask distance metric learning models for other applications. Finally, like other work on person re-identification by metric learning, distance metrics need to be relearned to tackle the variations in photographic and weather conditions. We will consider how to update the learned multiple metrics in the future. In future enhancement the person re-identification using lives videos and real time videos.

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