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DOUBLE THRESHOLD BASED METHOD FOR PERSON RE-IDENTIFICATION USING SIGNIFICANT COLOUR MATCHING IN THE SPATIAL CORRESPONDENCE REGIONS

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ABSTRACT

Person re-identification is a technique which has an objective to identify a person captured in different views in a community space monitored by network of numerous non-overlapping surveillance cameras. For better view over a region, surveillance camera is usually placed at a height more than person's height. With this set up, getting the facial features of the person becomes very difficult. Moreover, the cameras used will be of less resolution and other conditions including view angle, lighting conditions, occlusion and pose change are amongst the challenges which prevents to get essential facial features from the person's image. In this paper we have proposed double threshold-based person re-identification using significant colour matching in the spatial correspondence regions, which uses clothing colour as key feature to re-identify a person. Experiments are conducted on images in underground re-identification (GRID) dataset and results of the Cumulative Matching Characteristic (CMC) curve in evaluation with existing methods establish the efficiency of our method for person re-identification. With this proposed method we have achieved the first rank accuracy as 40.1% with the GRID database.

Keywords: surveillance, person re-identification, significant colour, K means algorithm.

1. INTRODUCTION

Person re-identification remains a task in computer vision which searches the same individual across different camera views. This task finds applications in video surveillance system used for security purpose. With the given image of individual called probe image, re-identification task explores the gallery for images containing the same individual captured from various cameras. Traditional way to identify a person is through the face recognition. But in the person re identification task, getting facial features from the images is highly difficult. The surveillance camera is fixed at the height more than that of a person to cover a larger area of surveillance. The cameras used for the surveillance are of very low quality which makes it very difficult task to get facial features from a person's image. As videos are captured in real time the person's pose may vary constantly. Illumination variations and camera viewpoint also remains big challenge for the person re identification. For these reasons appearance features like clothing colour remains a good choice of feature. In this paper significant colour of the clothing is used as important cue to identify a person. Figure-1 displays few example images from the GRID database. Figure-1 (a) displays the probe images and Figure-1 (b) displays corresponding gallery images. The probe images are the images which are used as a search images and the gallery images are the group of images in which search image is explored. Figure-1 shows sample images from GRID [23] dataset. Figure-1 (a) and 1 (b) (column wise) shows the same person captured in different camera view. The first person can be identified with his clothing colouring as red shirt and orange trousers. Similarly, second person can be identified with yellow colour and blue trouser and so on. For the fifth person even with the pose variation, person can be identified using his colour of the clothes.

Figure-1. Images from QMUL under Ground Re-identification (GRID) database. (a) Probe images. (b) Gallery images.

The contributions in this research paper are as follows:

- Finding the significant colours in the image using K-Means clustering algorithm. The clustering algorithm finds centroids which are the RGB colour value of the

significant colours present in the images.

- Mapping of the significant colour in its corresponding spatial locations. Representing each significant colour regions as separate class images.
- Comparison is done based upon the Euclidean distance measure between the significant colours and spatial correlation between the same class images.

The succeeding segments of the paper are organised in four sections: In Section- II, we have reviewed related research works in various aspects of person re identification. We detailed the proposed double threshold-based person re identification using significant colour matching in the spatial correspondence regions in Section -III. In Section-IV, the experiment results obtained on the images of standard database (GRID) are showed. Section-V includes the conclusion of the paper.

2. RELATED RESEARCH WORKS

In current years, person re identification has fascinated growing attention among researchers of computer vision community. Survey of these researches on person re identification has been analysed in three categories, i.e., feature, learning and sparse based.

A. Related works on Feature

Earlier works [1]-[6] used low-level features like the histograms of various colour spaces like RGB, YCbCr, HSV and HOG features for person re-identification. As single feature was not sufficient some works combined colour features with texture features. Tao, *et al* [7] concatenated Local binary pattern (LBP) descriptor which is a texture feature with HSV &RGB colour histogram values extracted from the overlapping blocks. In [8] local features along with clothing attributes are used for person re-identification. It also uses part-based approach to represent the appearance of a person. Y.Yang [9] introduced a novel method which uses the colour name and colours represented in different colour space as a feature representation. S.Liao *etal* [10] proposed features that evaluate the horizontal existence of maximally occurring local features to give a steady representation against viewpoint changes. Mu Gao [11] proposed a new feature which is the of union of basic weighted-histograms features extracted from overlying image stripes along with colour name descriptors. Song, Chunfeng [12] proposed binary masks are used for segmentation of body and the back-ground regions. These masks are used to decrease the background confusions and masks also contain features such as body shape information.

B. Related works on Learning based techniques

To learn similarity between the images common metric used is a distance measure. In [13] an adaptive ranking based support vector machine (ARSVM) is utilised for person re-identification that deals with the situation where absence of label name information of target images by using the matched & unmatched image pairs from cameras. Lianyang Ma [14] proposed a metric learning model based on Mahalanobis distance-based metrics to meet the challenges such as illumination differences, occlusion and pose differences.

C. Related works on Sparse based techniques

The problem with the distance learning model is that choosing an appropriate distance metric which can be used for all type of datasets is difficult. To solve the problem in distance learning method, Sparse based methods have been explored by researchers. Sparse representation-based classifier denotes the test images by making use of all the specified training samples. In [15], an iterative sparse discriminative classifier was used to increase the number of target rankings. Karanam [16] proposed sparse based method which takes the viewpoint variation into attention and used a trainable dictionary which is invariable to view point changes, for each probe and gallery pair images.

3. PROPOSED METHOD

In general, people wear coloured clothes in a public place and the colour cue provides significant role in identifying the person. The strong inspiration for using colour of the clothing to identify a person is that it can be robust to viewpoint variations in normal illumination conditions. The colour cue is widely used in applications like person re-identification, image retrieval etc. The colour of clothing gives the major clue to identify the person. The flow chart diagram of the suggested method is given in the Figure-2. Probe images and Gallery images are pre-processed using high pass filters. This helps to sharpen the edges which are blurred. In the next step 'K' means clustering algorithm is used to obtain the significant colours in the images. It divides the image into regions according to the significant colours. This is done by clustering the pixels with similar colour to same category.

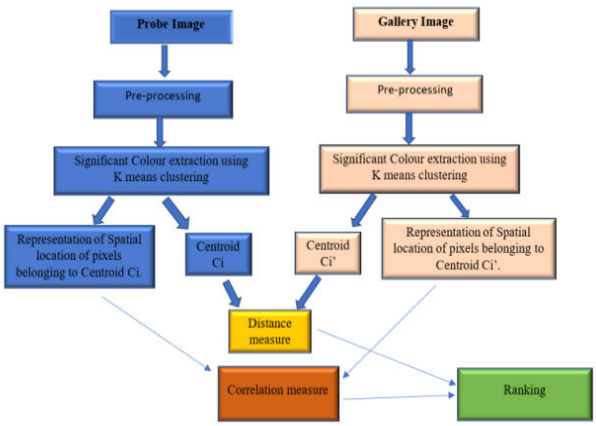


Figure-2. Flow diagram of the proposed algorithm.

A. 'K'-means Clustering Algorithm

'K'-means clustering algorithm is one of the renowned clustering algorithms used for image segmentation. This clustering algorithm is an unsupervised learning algorithm. This algorithm takes the 'k' parameters as inputs, and splits total 'n' objects into 'k'

clusters in such a way that the resulting intra cluster distance is low but the inter cluster distance is high. Similarity measure is a distance which is measured inside a cluster with respect to the mean (average) value of the objects known as cluster's centroid. Initially, it chooses random value of 'k' objects as a cluster mean. Then each other object in the given set, is allotted to the cluster to which it is the most alike, dependent on the distance measure between the object and the cluster mean. It then calculates the updated mean for each cluster. The above process is an iterative process, which continues until the given criterion function converges.

The proposed algorithm for clustering to find the significant colour:

Input: RGB values of the N Pixels of input image.

Let there be 'k' number of clusters; N be total no of pixels present in the image.

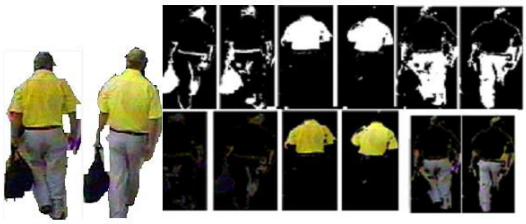
Output: k cluster centroids which represent RGB value of a pixel.

- **Step 1:** Initialize the cluster center which is RGB value.
- **Step 2:** Every pixel is allotted to the cluster in which the distance measure between the RGB value of pixel and the cluster centre is minimum. It results in groups of pixels with similar colours.
- **Step 3:** Change the initial centroid to the mean of the pixel values in a group.
- **Step 4:** Minimize the distance measure in accordance to the new value of centroids. Thus, observations will change from one group to another. Repeat until no pixel changes groups.

B. Spatial Correspondence

In order to map the pixels belonging to the centroid C_i , the pixels belonging to the cluster C_i in the image I_1 are represented with white pixels while the other pixels in the image are represented as black. This resultant binary map image represents the spatial locations of the pixels fitting into the cluster C_i in the image-I_1. Same procedure is followed for pixels belonging to the cluster C_i' in the image-I_2. The binary map image represents the spatial locations of the pixels fitting to the cluster C_i' in the image I_2. The Figure-3.(c) shows the binary map images of cluster C_i and C_i'. By this representation person's image is clustered into regions belonging to significant colours. The binary map image for each centroid C_i is represented as separate class. The comparison is done between the same class images of $I_1$and I_2 and measure of correlation is found.

If the correlation is greater than threshold T_2more likely I_1 and I_2 are same images.



(a) (b) (c)

Figure-3. (a) Probe image (b) Gallery Image(c) Binary map of Spatial location of each pixel belonging to centroid represented as separate classes.

4. EXPERIMENTAL RESULTS

A. GRID Dataset:

GRID [23] dataset belongs to Queen Mary University of London which has pedestrian images captured in underground terminal. The dataset includes 250 pairs of individuals' images captured in a challenging lighting conditions. The images in this data set are captured out of 8 diverse low-quality surveillance cameras, which create a great challenge. It has two sets of images one for probe and other for gallery with a total of 250 matched image pairs, and also 775 additional individual images with no match. For the purpose of experimental calculations, the dataset has 10 trial partitions. The images captured under inter-object occlusion and a high view-point variation makes it really tough.

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Algorithm: The dominant colour region extraction algorithm is shown as follows:
Input: k: the number of clusters, N: No of pixels in the image. Let I_1 be the probe image and be the I_2 Gallery image; Step 1: Images are filtered using high pass filter. This sharpens the edges. Region of interest alone is separated manually. Step 2: Apply k means algorithm to I_1, I_2. Let F, F' be the set of k centroids, which represents significant colours of I_1, I_2 respectively. Step 3: Represent the pixels belonging to Centroid C_i and C_i' as binary images Si, Si'. This represents the spatial location of pixels belonging to the Centroid C_i, C_i'. If the correlation between the 2 binary images are positive the spatial locations of the pixels belonging to centroid C_i and C_i' are likely to be same. Step 4: The Euclidean distance measure is found between the centroids C_i and C_i' which gives the measure of distance between the colours in the regions belonging to similar spatial locations. If the distance is lesser than the threshold T_1 and correlation measure greater than T_2 then I_1 and I_2 are more likely to be the images of the same person. Step 5: Ranking of the gallery images with the Euclidean distance and Correlation measure.

B. Experiments on GRID dataset

Experiments are done using Matlab on GRID dataset. It is a difficult work for Re-identification algorithms to perform on the GRID dataset as the images are obtained from a complicated scene of the populated underground terminal. As the images are highly influenced by lighting variations, we have fixed the threshold T_1 as 35 and the correlation measure T_2 as 0.1. Figure-4 (a) shows the probe and the gallery image of a same person. The threshold T_1 for the colour difference is measured as 31.7. The correlation measure (Threshold T_2) between the binary map image is measured as 0.36. Figure-4 (b) shows the probe and the gallery image of a different person. The threshold T_1 for the colour difference is measured as 45.7. The correlation measure (Threshold T_2) between the binary map image is measured as -0.02.

Figure-4. Binary map of Spatial location of each pixels belonging to each centroid and its colour map. (a) Probe and Gallery images representing same individual. (b) Probe and Gallery images representing different individuals.

The gallery images are ranked based with respect to the distance score of the centroids and correlation measure between the spatial correspondence regions.The Figure-5 shows some of the results.

Figure-5. Probe and correspoding ranked gallery images based on threshold score.

We conducted experiments and compared the results with the existing methods. Table-1 shows the comparison results. We evaluate the matching performance using Cumulative Matching Curve. Our results are compared with Polymap [19], LOMO+XQDA [20] and SCSP [21]. In Polymap [19], authors use the polynomial-kernel feature based map to define the sample image description. Further to achieve improved similarity learning results a negative semi definite regularization technique is introduced. In SCSP [21] takes the benefit of the spatial limitations and offers framework which finds similarities. In [22] authors use weights based fusion approach which connects the sparse representation along with collective representation. Figure-6 illustrates the comparison of Cumulative matching characteristics curves of different existing methods with our method.

Table-1. Comparison of performance at various ranks.

Methods	GRID				
	Rank 1	Rank 5	Rank 10	Rank 15	Rank 20
PRDC[17]	11.12	26.08	35.76	41.76	46.56
Mrank-Ln(PRDC)[18]	10.88	24.96	35.84	41.44	46.40
Polymap[19]	16.3	35.8	46.0	47.3	52.8
LOMO +XQDA[20]	16.6	33.8	41.8	46.8	52.4
SCSP[21]	24.2	44.6	54.1	63.6	65.2
WISCR [22]	24.8	45.4	54.1	57.8	68.9
Ours	40.1	62.2	72.8	78.4	82.4

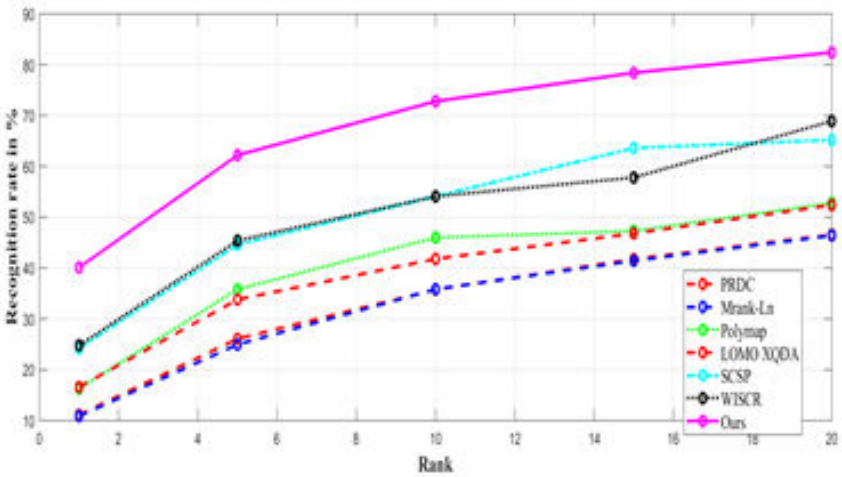

Figure-6. Comparison using cumulative matching curve with existing methods.

5. CONCLUSIONS

The proposed double threshold-based person re identification using significant colour matching in the spatial correspondence regions uses clothing colour as key feature to re-identify a person. It uses K means algorithm which is an unsupervised algorithm, which does not require labelling for training. As it is based on the colour of the clothing, it is invariant to pose variations. The spatial correspondence between the regions ensures that the colour is present in upper or lower part of the person's body. We perform the experiments on a challenging dataset which is captured in various lighting conditions and pose variations. Our method significantly improves first rank accuracy to 40.1 % which is significantly higher than the existing methods.

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