

Features Accumulation on a Multiple View Oriented Model for People Re-Identification

J. García¹, A. Gardel¹, I. Bravo¹, J.L. Lázaro¹, C. Kambhamettu²

¹ Department of Electronics, University of Alcalá, Alcalá de Henares, 28871 Madrid, Spain.

² VIMS Laboratory, Dept. of Computer and Information Sciences, University of Delaware, Newark, DE 19716, United States.

Abstract

People re-identification process provides relevant information in order to understand the scene. In this paper, we present a multiple-view oriented model for performing people re-identification in a camera network. An appearance model for different perspectives is generated from people trajectories. Global and local features besides path orientation are extracted from each person's image, given a short-term tracking. Experimental results based on different sets of features demonstrate the effectiveness of our system.

Categories and Subject Descriptors (according to ACM CCS): I.4.8 [Image Processing and Computer Vision]: Scene Analysis—

1. Introduction

People re-identification is the visual recognition of the same person in disjoint camera views, considering a certain set of different identities. The knowledge about the identities of people enables a system to fully understand the scene [BCBT11]. Surveillance systems where a camera network is monitoring different scenarios represent a perfect example to perform these tasks. Typically, this type of surveillance network is composed by different cameras with non-overlapping field of views located in a large area. To address this goal, a feature set is extracted from each person detected on a captured image, a process known as identification. The features to model the appearance are classified into two groups: global and local. The difference between them is the area where the feature is applied. Local features focus on information where there are interest points while global features are present in a large extent of a person. Typically, a set of features that defines a person is referred to as signature. Re-identification process is carried out through a similarity measure comparing signatures between different views. Under non-overlapping camera views, several problems are involved to the re-identification process. Different perspectives are captured when a person crosses different cameras; normally four poses are defined: front, back, left and right side. This aspect needs to be considered when using different views to create a signature. The people appearance

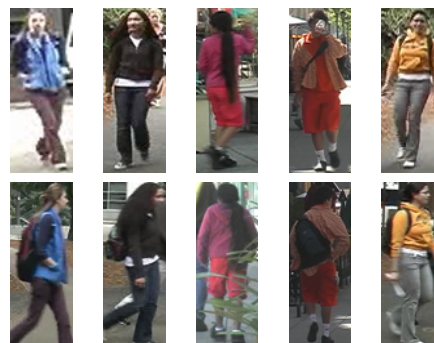


Figure 1: Examples of VIPeR dataset [GT08]. Each column is one pair of images corresponding to the same person.

may be affected by lighting changes between different locations. The fusion of global and local features helps create more robust signatures. Temporal and spatial constraints can reduce effects of transition time between disjoint cameras. Each camera captures an uncontrolled environment from a distance; this means that the recognition of biometric aspects such as face, eyes or gait detection, provide low reliability due to difficult segmentation, use of low resolution and low frame rate video. In the Figure 1, some examples on the problems earlier described are shown. Some methods

[HRKB12] extract features from multiple images and use learning process in order to obtain a signature more suitable with respect to perspective changes. Finally, there are contributions more focused in a robust distance measure which try to quantify and differentiate features by learning the distance measure that is most likely to get correct matches [ZGX12].

In this paper, we propose a multiple view oriented model to perform people re-identification in a camera network where an appearance model for different perspectives is generated from the people trajectory. The paper is organized as follows. In Section 2, previous related works are reviewed with respect to the subject under discussion. In Section 3, we present our contribution in the people re-identification field, and finally, in Section 4 an analysis of the results processing public datasets is provided.

2. Related Work

Most contributions generate a signature based on appearance model from single or multiple images corresponding to same person from a set of features. These can be classified into two groups: global and local features. Typically, global features are obtained via chromatic histogram from different color spaces [CAK10]. Texture feature extraction is other option to characterize the people appearance model [GT08]. These features are more stable than color features so the signature is more independent with respect to viewpoint changes. Other type of signatures is complemented by local features. [OSP09] use local histograms from *HSV* color space. They are determined in areas around specific points of interest. Furthermore, each region of interest is used by a *SURF* (Speeded Up Robust Features) descriptor. Other local features such as *Haar-like* features are extracted to define a signature as in [BCBT10]. [BS11] use gradient location and orientation histogram (*GLOH*), combining ideas from both *SIFT* and shape context.

On the other hand, local features are descriptors applied over local interest point such as Harris detector, Hessian-Laplace, etc. Other type of descriptors used to create a signature are covariance descriptors as proposed in [BCBT11]. Using the dense descriptors philosophy, an overlapping grid structure is applied to the image. A cell is defined at each point of the grid where the covariance descriptor is calculated, so the signature is composed by a large vector of covariance descriptors. Research work in [CAK10] determine the silhouette from background/foreground update process in order to only include information belonging to the person. Some authors propose the body segmentation in parts. In [FBP*10] the body is divided into three parts: legs, trunk and head. Each extracted feature is weighted according to the body part and with respect to the distance between the half body (vertical orientation) and the feature location. Another possible classification of appearance models takes into account the number of person images in order to create the signature. Single shot methods [GT08] only use one image

of the person to extract features, while an image set is required in multiple shots methods [BCBT11]. Selection of a single or multiple method depends on the availability/use of tracking information. Multiple shots methods form a signature more independent than single shot methods with respect to captured viewpoint or lighting changes. In contrast, fusion techniques are necessary to combine information from multiple images. The major problem in the re-identification methods are variations in appearance when a person is captured from different perspectives. Given a pair of signatures corresponding to a remarkably different viewpoint, the match between local features decreases and only the influence with respect to global features provides similarity in the matching process. To mitigate this problem, we propose a multiple view oriented model which represents a signature composed of different images. Each image of the model represents a different updated viewpoint.

3. Multiple View Oriented Model

3.1. Model Overview

Since a camera provides a short-term tracking of people crossing the scene, multiple images may be used to model the people appearance. These methods, referred to as multiple shots, merge the information extracted from all the images to create a signature more suitable to perspective or people orientation changes. We propose a multiple view oriented model (*MVOM*) which represents a signature composed of different images where each one provides an updated view of the person. The model is composed of different feature vectors, each one extracted from an update view. Two events can occur to add an image to the model, these are explained below:

- *Direction changes*: The trajectory generated by a person across the scene captured by a camera may contain direction changes due to static objects which are located in the scene, crosses between people or his/her own trajectory. These situations are exploited by our *MVOM* to obtain different perspectives of the person and are quantified using an orientation parameter according to camera location. An image is added to the model when it is detected a strong change in a short period of time or a weak change in a large period of time.
- *Periodic acquisition*: Images are incorporated into the model which are complementary, at every certain period of time. Thus, several images with the same orientation are collected to obtain an appearance model that is less dependent. This type of data acquisition for appearance model leads to a larger database of possible similar images that could be later refined to reduce amount of data to be processed.

3.2. MVOM Parameterization

Formally, the common re-identification process is defined as follows. Let $\mathcal{C} = \{1, 2, \dots, N_C\}$ is a set of non-overlapping

camera views where N_C is the total number of camera views involved in the re-identification process. Assuming that a set of people images $\mathcal{I} = \{i_n \mid n = 1, 2, \dots, N_I\}$, where N_I is the total number of images obtained from \mathcal{C} and each $i_n \in \mathbb{R}^{W \times H}$ where $W \times H$ is the size of an image, it is defined $\mathcal{P} = \{1, 2, \dots, N_P\}$ as a set of labels where N_P is the total number of labels. Each element \mathcal{P}_n represents a single person across the field of view captured by a camera network. The signature of an image i_n belonging to an individual is represented by a features vector $\mathbf{x}_n \equiv \mathbf{f}(i_n)$. The person which corresponds to the image i_n must satisfy $y_n \equiv y(i_n)$ to correspond to a label y_n . The set of images representing the same person is defined as $\mathcal{S}_z \subseteq \mathcal{I}$ where each image $i_n = \{i \mid y(i) = z\}$. Given an image from the database and a new candidate image in order to share the same label, their feature vectors should match, which is given by a distance function expressed as:

$$M(y_{n1}, y_{n2}) = m(\mathbf{f}(i_{n1}), \mathbf{f}(i_{n2}))$$

where $m(\cdot)$ is a certain specific function to measure the similarity between two signatures. Thus, depending on the descriptors chosen, the function $m(\cdot)$, should be different.

In our paper, we define subsets \mathcal{S}'_z where all images belong to the same label from short-term tracking. The subset size depends on two factors: time within the field of view of the camera, and trajectory changes of the person. If the tracking is robust the same label is directly assigned to the whole subset. We propose to extract a features vector and an orientation value $\mathbf{x}_n \equiv [\mathbf{f}(i_n) \quad \theta(i_n)]$ from each image which has been added to the model. In this way a subset \mathcal{S}'_z can be expressed as:

$$\mathcal{S}'_z = \begin{bmatrix} \mathbf{x}_1 \\ \vdots \\ \mathbf{x}_N \end{bmatrix} = \begin{bmatrix} \mathbf{f}(i_1) & \theta(i_1) \\ \vdots & \vdots \\ \mathbf{f}(i_N) & \theta(i_N) \end{bmatrix}$$

Given a re-identification process between two subsets \mathcal{S}_{z1} and \mathcal{S}_{z2} as the query subset and a selected subset from available subsets corresponding to a label, respectively, the function $m(\cdot)$ is calculated for each pair of vectors $\mathbf{f}(i_n)$ within a common range of $\theta(i_n)$. In cases where a common range is not possible, an all-to-all matching is calculated. The best match is selected in order to join the query subset with the same label.

3.3. Accumulation of Global and Local Features

Different steps are necessary in order to extract a set of features from an image where multiple people can appear. A background/foreground segmentation algorithm is the first step to detect all non-static objects as proposed in [CAK10] where a method based on an adaptive spatial-colorimetric model is presented. Moreover, an estimator of orientation from the short-term tracking algorithm is responsible to define an orientation scalar value between the person trajectory

and the camera. In this paper, we assume masks of silhouette that define only information of the person to compute the set of features and an orientation value for each silhouette is established that appears in the image. Different features are accumulated in a vector in order to encode the visual appearance of a person. A feature vector is constructed from each image, thus a label of person is composed by multiple feature vectors.

4. Experimental Results

In this section, we present different experiments to evaluate the proposed multiple view oriented model. The results are presented through two common curves used in people re-identification: Cumulative Matching Characteristic (CMC) curve and Synthetic Recognition Rate (SRR) curve. The CMC curve provides the recognition percentage which represents the expectation of finding the correct label within major matched labels. Furthermore, the SRR curve provides the probability that any label between the best matched labels is correct. The dataset used is proposed in [MM12]. It is composed of three non-overlapping cameras in real scenario where 61 different individuals cross the entire scene. Each camera capture images with a resolution of 320x240 pixels and a frame rate of 1 frame per second. The size of people images is normalized to 96x48. This dataset includes different viewpoints of the people and lighting changes. A short-term tracking is collected for all people in each camera. Thus, the overall re-identification process is composed of 183 subsets \mathcal{S}'_z . Other benchmark datasets, such as VIPeR, cannot be used to show comparisons as it only provides two single views of each person. To compare the effectiveness of the proposed model with respect to other contributions, two sets of features are used to implement the multiple view oriented model proposed in [FBP*10] and [MM12]. Also the re-identification functions $m(\cdot)$ proposed by the authors are used, in order to show the advantages of using a multiple view oriented model as proposed, without improving the features of individual images. The first set of features is composed of weighted color histograms, maximally stable color regions (MSCR) and recurrent high-structured patches. All features are weighted with respect to vertical axis and classified in two principal regions. The area corresponding to the head is not taken into account to extract features because it normally contains very few pixels providing little information about the person. The set proposed in [MM12] exploit three local features: SIFT features, pyramid of histograms of orientation (PHOG) and Haralick texture features. The authors implement the same body partitioning. SIFT features are used to extract the chromatic appearance from HSV color space in different interest points. The PHOG is calculated in three levels and they are accumulated into a single oriented histogram. Haralick texture features are determined in the regions where more information is concentrated (legs and trunk regions). Figure 2 represents CMC and SRR curves. Our methods are compared with single-shot case proposed

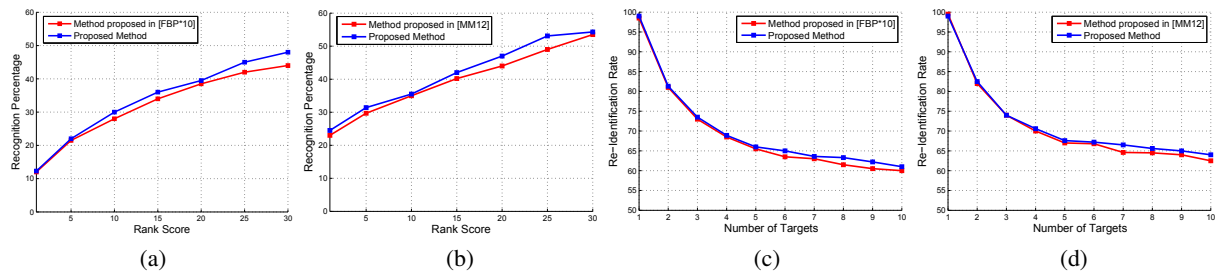


Figure 2: Performances on dataset proposed in [MM12]. In (a) and (c) the proposed method is compared with [FBP*10]. In (b) and (d) the proposed method is compared with [MM12].

in [FBP*10] and [MM12], respectively. The multiple view oriented model performs a single-shot matching process using a query image against a database image with similar orientation. The major problems are lighting changes and the low resolution of images. Consequently, poor feature vectors are obtained in each pair of images resulting in a calculated distance that is not satisfactory. *Rank Score = 1* is the rank score result which represents the correct re-identification result. In figure 2.a, the proposed method provides a recognition percentage of 11.3% while the method proposed in [FBP*10] presents a 10% in *Rank Score = 1*. Moreover, the difference between recognition percentages increase in other rank score values. A similar case occurs in figure 2.b, where the proposed method provides a recognition percentage of 22.9% and the method proposed in [MM12] have a 21% in *Rank Score = 1*. The proposed model reduces perspective changes as multiple vectors with different orientations represent a more robust appearance of the person.

5. Conclusions

In this paper a multiple view oriented model is presented to carry out people re-identification process. Due to variations in appearance from different perspectives of the person, we propose a model composed of different views of the person. Each image is represented by a features vector and a parameter of estimated orientation, extracted from person trajectory. The proposed model works without training stages to carry out the re-identification process and is not necessary to have a priori knowledge about the full dataset. Different experiments have been performed with two feature sets proposed by other authors to provide a reliable comparison. The major problems in the re-identification process are due to lighting changes and low image resolution. However, problems related to the appearance variation due to perspective changes have been reduced.

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