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BiMPeR: A Novel Bi-Model Person Re-identification Method based on the Appearance and the Gait Features

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Abstract

Person re-identification presents an active research area for intelligent video surveillance systems. The purpose is to find the same person from disjoint camera views at different times and locations. In this paper, we propose a novel Bi-Model Person Re-identification method (BiMPeR) that combines the appearance and the gait features to improve the re-identification performance and to handle the problem of similar appearances. The main idea is to prove the complementarity of these two modalities to extract a discriminative person signature for the re-identification problem. A score fusion method was adopted to combine these two modalities to reflect the impact of each one on the final decision. Experiments were performed on the CASIA-B database revealing promising results and showing the effectiveness of the proposed method against state-of-the-art uni-model methods.

Keywords: Person re-identification; Appearance features; Gait features; Score fusion

1. Introduction

Nowadays, intelligent video surveillance systems present one of the most active research areas that aim to automatically monitor a large camera network. Person re-identification presents a fundamental task for these intelligent applications that aims to retrieve a person of interest across multiple cameras [4, 6]. It consists of sorting the individuals recorded by the different cameras of the network (*i.e.* gallery set) in descending order according the their similarity to the probe person. Then, the identity of the most similar one is assigned to the probe person. The efficiency of the re-identification method largely depends on the designed features to model each person in the network. These features should provide a discriminative profile to handle the uncontrolled acquisition conditions of the different cameras in terms of pose and viewpoint variations, lighting variation, low-image resolution, partial occlusion and sensor variations.

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Fig. 1. Example of people with similar appearance characteristics.

Most of the state-of-the-art methods have proposed a unimodal person re-identification system based either on biometric or appearance features. On one hand, several person re-identification methods have addressed the problem by extracting biometric modalities (*i.e.* face and iris). Nevertheless, these methods displayed a low performance as they require high resolution images from a close distance range. To this end, gait features are considered as a suitable biometric modality to solve the person re-identification problem by identifying people via their walking pattern without subject cooperation [3, 4]. On the other hand, appearance features aim to re-identify a person based on his visual characteristics as they provide uniqueness over limited period of time [1, 20, 14]. However, the main disadvantage of appearance features is that people may wear similar clothes (*i.e.* dark clothes in the winter or white apron in the hospital), as shown in fig. 1. Thus, using both appearance and gait features could improve the re-identification task thanks to their complementary.

In this paper, we propose a novel Bi-Model Person Re-identification (BiMPeR) method that combines both appearance and gait features in order to improve the re-identification performance and to handle the problem of similar appearances. The appearance characteristics are modelled based on the Multi-Level Semantic Appearance Representation (MLSAR) descriptor [6] that extracts both low-level features and semantic attributes. The gait characteristics are modelled based on the Gait Dynamic Selection (GAIDS) descriptor [4]. A score fusion-based method is adopted to combine these two modalities. Different experiments have been conducted to give a thorough evaluation of our BiMPeR method based on the CASIA dataset. Firstly, we evaluated the performance of the adopted score fusion method against the state-of-the-art information fusion levels (*i.e.* score fusion based methods, and rank fusion based methods). Then, a comparison with uni-model person re-identification methods is performed.

The remainder of this paper was organized as follows: section 2 presents the related work. Section 3 introduces the proposed Bi-Model Person Re-identification method. The experimental results are presented in section 4. Finally, section 5 recapitulates the conclusions.

2. Related work

In the literature, state-of-the-art person re-identification methods can be divided into three main groups: (1) Biometric-based methods, (2) Appearance-based methods and (3) Hybrid based methods.

Conventional biometric modalities (*i.e.* face and iris) perform a great job in recognizing people, but they are not suitable for person re-identification as they require high resolution images from a close distance range. Further, they require a specific body profile to detect the discriminative biometric features. Further, criminals take extra precautionary measures to avoid being recognized by surveillance technology. This comprises wearing gloves to hide their fingerprints or fully cover their faces. Gait is considered as a biometric modality that aim to identify people via their walking pattern by unobtrusive methods and without cooperative subjects [3, 4]. Lately, it has been considered as an interesting modality to perform the re-identification task. Some methods have concentrated on model-based methods [2, 11] and others on model-free methods [9]. In model-based methods, the representation of human body is acquired using the model parameters and modelled by different geometrical shapes. Whereas, in model-free methods, silhouette images are directly manipulated to extract spatiotemporal motion information and various statistical features.

On the other hand, appearance-based methods aim to re-identify a person based on his visual characteristics as they exhibit uniqueness over limited period of time. Some methods have focused on extracting a local feature representation to describe each person based on low-level features [1, 20] or on deep features [14]. Others have relied on the semantic attributes, *i.e.* mid-level features, that consists of describing the appearance in terms of worn clothes and carried objects [22, 23, 16]. Recently, some methods [15, 6] have combined the semantic attributes with local feature representation to perform the re-identification task to extract more discriminative profile.

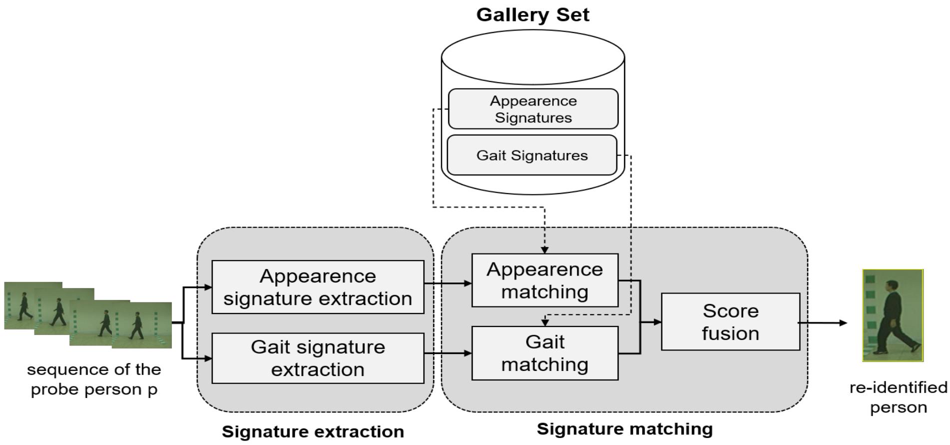

Fig. 2. The flowchart of the proposed Bi-Model Person Re-identification method.

However, the major drawback of appearance-based methods is that people may wear similar clothing styles such as dark clothes in winter or white apron in the hospital, as shown in fig. 1. In this case, appearance-based methods may not be reliable enough for person re-identification problem.

Hybrid based methods consist in combining both appearance and gait features to perform the re-identification. Liu et al. [18] have proposed a framework that relies on hierarchical feature extraction and matching. The descriptor is composed of HSV histogram and Gabor feature as appearance feature and GEI image as gait feature. Further, Li et al. [17] proposed a PROgressive Person ReIDentification framework (PROPRID) that exploits the multi-level appearances and human gait features in video surveillance systems. However, two main issues need to be addresses for hybrid-based method. Firstly, the choice of the descriptors to model each modality, secondly, the choice of the information fusion method to determine the impact of each modality on the re-identification performance.

3. Proposed Method

In this paper, we propose a Bi-Model Person Re-identification (BiMPeR) method that aims to re-identify a person across a large camera network. The proposed method relies on two main steps, as shown in fig. 2: (1) Signature extraction and (2) Signature matching. The first step aims to extract a discriminative signature for a probe person p by modelling both the appearance and gait features. The second step aims to match the probe person p against the gallery in order to find the corresponding match in the gallery set.

3.1. Signature extraction

This step aims to extract the relevant person characteristics from his trajectory to provide a discriminative profile to handle the fundamental challenges of uncontrolled acquisition conditions. We propose to model the person's signature based on two complementary descriptors, *i.e.*, the MLSAR and the GAIDS descriptors. Hereafter, the signature extraction step relies on two sub-steps: (1) Appearance signature extraction and (2) Gait signature extraction.

3.1.1. Appearance signature extraction

The goal is to encode the visual appearance characteristics for a given person into an appearance signature, AS, based on the MLSAR descriptor [6]. This signature models two levels of appearance characteristics based on two descriptors. The former relies on the Multi-Channel Co-occurrence Matrix (MCCM) descriptor [5] that extracts low-level features in terms of color and texture information. And the latter relies on the Semantic Body Trait (SBT) [8] descriptor that extracts the semantic attributes, *i.e.* mid-level features, in terms of worn bags, carried objects.

MCCM extraction: this descriptor models the low-level appearance characteristics in terms of color and texture characteristics from the salient body stripes for a given person image. It starts by dividing the person image into six equalized horizontal body stripes for the person p (*i.e.* BS_p) to capture the different body area (*i.e.* Head, Upper Torso, Lower Torso, Upper Legs, Lower Legs, and Feet). In [5], body stripes corresponding to Upper Torso, Lower Torso, Upper Legs, *i.e.* $\left\{UT_p, LT_p, UL_p\right\}$, have been proved to depict the most discriminative appearance characteristics under uncontrolled acquisition conditions. Therefore, their low-level characteristics for these Salient Body Stripes (SBS) have been modelled by extracting the MCCM descriptor. It calculates the adjacent frequency between two color values in the HSV color space for a given body strip, as expressed in (1).

$$MCCM_p^{SBS_i}(i,j,k) = \sum_{x=1}^{N}\sum_{y=1}^{M}\begin{cases}1, & SBS(x,y,k) == i \wedge SBS\left(x+\Delta_x, y+\Delta_y, k\right) == j\\ 0, & otherwise\end{cases} \quad (1)$$

Where: k denotes the color component (H, S, V), Δ_x and Δ_y are the offset.

More specifically, MCCM descriptor was calculated according to the direct neighbor by considering four directions (0°, 45°, 90°, 135°). It encodes the distribution of the intensities and ignores the relative position of neighboring pixels that make him rotation invariant.

SBT descriptor: this descriptor models the mid-level appearance characteristics in terms of a semantic appearance description for a given person based on a vocabulary of 14 semantic attributes. It describes the appearance characteristics in terms of anthropometric characteristics, clothes style and accessories patterns. The choice of vocabulary terms relies on the same description vocabulary that we use to describe the appearance of each other in a crowded place or from a far distance [7]. More specifically, the SBT descriptor is composed of a set of pre-trained classifiers where each one predicts the presence probability of a specific attribute in a given person's image [8]. These attribute classifiers have been trained during an off-line stage that relies on a data mining process to correctly classify an attribute. Then, these trained attribute classifiers are gathered together to conduct the Semantic Body Traits descriptor. So, for a given person image, the SBT descriptor automatically generates the semantic appearance description, where each classifier predicts the probability of the concerned semantic attribute that varies between 0 and 1. If the value is close to 1 it indicates the presence of the attribute otherwise it is considered as absent.

Finally, the combination of these two extracted descriptors (*i.e.* MCCM and SBT) produces the MLSAR appearance signature.

3.1.2. Gait signature extraction

The goal of this second sub-step is to encode the gait information for the detected walking person based on the GAIDS descriptor.

GAIDS Descriptor: this descriptor models the human walking properties for a given person. In our work, we opted for a free model method, and particularly a period based one relying on the Gait Energy Image (GEI). GEI can be considered as the most used gait representation for biometric recognition purposes. It represents a spatiotemporal description of a periodic person's motion. This period is commonly identified as a gait cycle, composed of two phases swing and stance, beginning with the heel strike of one leg and finishing when the same foot touches the ground. The gait cycle is represented by the set of N silhouettes between two consecutive mid-stances of the same type. Given N binary gait silhouette image frames $S_t(x,y)$ representing a gait cycle, the Gait Energy Image is defined by equation (2).

$$G(x,y) = \frac{1}{N}\sum_{t=1}^{N} S_t(x,y) \quad (2)$$

Where: t is the frame number in the sequence (point in time) and (x,y) are the pixels coordinates.

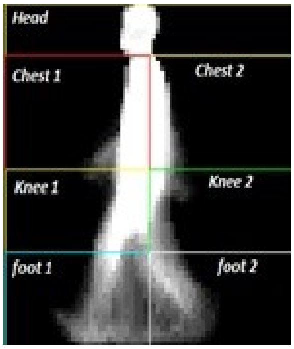

Fig. 3. The divided GEI into seven parts.

GAIDS captures the relevant and significant features for gait characteristics. Therefore, the obtained GEI is subdivided into seven parts which are head, chest1, chest2, knee1, knee2, foot1 and foot2 as shown in fig. 3. Then, on each part, we apply the P-LBP (Partial Local Binary Pattern) to encode local color and texture characteristics. The GEI has two main regions: the first is static with high-intensity pixels and includes head, chest1, chest2, knee1 and knee2; and the second is dynamic with low-intensity pixels and corresponds to the lower part of the body (*i.e.*, foot1 and foot2). P-LBP extends the conventional LBP (Local Binary Pattern) [13] by thresholding the $3*3$ neighborhood of each pixel with the center value and considering the result as a binary number (0 or 1) which is defined by equation 3.

$$P-LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{3}$$

where: i_c corresponds to the value of the center pixel (x_c, y_c), i_n to the value of the eight surrounding pixels, and function $s(x)$ is defined by equation (4).

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{4}$$

3.2. *Signature matching*

We compute the similarity score, $d(S_p, S_g)$, between the probe's signature S_p and each gallery person's signature S_g to determine the corresponding identity. To this end, we start by computing a similarity score for each modality separately, *i.e.* $d_{MLSAR}(AS_p, AS_g)$ and $d_{GAIDS}(GS_p, GS_g)$. Then, these two scores are combined based on score fusion method.

3.2.1. *Appearance signature matching*

The MLSAR similarity score, $d_{MLSAR}(AS_p, AS_g)$, between the probe person p and a gallery person g is obtained based on the fusion between the similarity score of the SBT descriptor, $d_{SBT}(AS_p, AS_g)$, and the similarity score of the MCCM descriptor, $d_{MCCM}(AS_p, AS_g)$, as expressed by equation (5).

$$d_{MLSAR}\left(AS_p, AS_g\right) = w_{SBT} * d_{SBT}\left(AS_p, AS_g\right) + w_{MCCM} * d_{MCCM}\left(AS_p, AS_g\right) \tag{5}$$

where: w_{SBT} and w_{MCCM} denote the assigned weights to SBT descriptor and MCCM descriptor, respectively.

For SBT matching, the similarity score is computed based on the sum of the corresponding a posteriori probabilities product, as formulated in equation 6.

$$d_{SBT}\left(AS_p, AS_g\right) = \sum_{a \in 1..A} p(a/p) * p(a/g) \tag{6}$$

Where: A denotes the semantic attribute number.

For MCCM matching, the similarity score is computed based on the sum of the corresponding body parts similarities using the Bhattacharya distance, as formulated in equations (7) and (8):

$$d_{MCCM}\left(AS_p, AS_g\right) = \left(\sum_{SBS \in \{UT, LT, UL\}} d\left(AS_p^{SBS}, AS_g^{SBS}\right)\right) / \|SBS\| \tag{7}$$

$$d\left(AS_p^{SBS}, AS_g^{SBS}\right) = \sum_{x=1}^{X} \sqrt{AS_p^{SBS}(x) * AS_g^{SBS}(x)} \tag{8}$$

Where: X is the size the MCCM feature vector.

3.2.2. *Gait signature matching*

This step aims to compute the GAIT matching score, $d_{GAIDS}(GS_p, GS_g)$, between the probe person p and a gallery person g based on the Euclidean distance, as formulated by equation 9.

$$d_{GAIDS}(GS_p, GS_g) = \frac{\sum_{i=1}^{nbparts} d_{GAIDS_i}}{nbparts} \tag{9}$$

where: *nbpart* represents the parts number in the Gait Energy Image.

3.2.3. *Score fusion*

The re-identification problem is defined as a maximum likelihood estimation problem [1], where the identity of the most similar gallery person is assigned to the probe, as formulated in (10).

$$id(p) = \underset{g \in 1..G}{argmax}\, d\left(S_p, S_g\right) \tag{10}$$

Where: G is the size of the gallery set.

Fig. 4. Example of person's images with different conditions in 90 view angles.

$d\left(S_p, S_g\right)$ represents the final matching score obtained by combining the similarity scores obtained by these two modalities, *i.e.* appearance and gait features, based on a score fusion method, *i.e.* the sum rule, as expressed by equation (11).

$$d\left(S_p, S_g\right) = d_{MLSAR}\left(AS_p, AS_g\right) + d_{GAIDS}\left(GS_p, GS_g\right) \tag{11}$$

4. Experimental Results

In order to evaluate the performance of the proposed method, we carried out two series of experiments on the CASIA Gait Dataset B [24] that covers several challenges for person re-identification problem. Different experiments have been conducted to give a thorough evaluation of our proposed person re-identification method.

Firstly, we assessed the performance of the method against information fusion levels (*i.e.* score fusion methods and rank fusion methods). Secondly, we evaluated the effectiveness of the proposed method against uni-model person re-identification methods which are based on appearance and gait descriptor separately. But first, the dataset and the evaluation metrics are presented.

4.1. Experimental setup and evaluation metrics

The CASIA Gait Database B have been produced by the Institute of Automation, Chinese Academy of Sciences (CASIA) [24]. It contains 124 persons where each one is presented by 10 walking sequences. More specifically, this dataset comprises three types of walking sequences for each subject. It consists in Normal Walking Sequences (NWS), Carrying Bag Sequences (CBS) and Wearing Coat Sequences (WCS), as can be seen in fig. 5.

For each experimentation, we randomly selected 51 persons where for each one we randomly selected one sequence to build the gallery set and one sequence to build the probe set. This procedure was repeated 10 times as proposed in [4] and the average performance over the 10 trials were reported. For the evaluation, we relied on the common person re-identification evaluation metrics: the Rank-n accuracy and the nAUC (normalized Area Under the Curve) extracted from the CMC curve (Cumulative Match Characteristic). The CMC presents the most common metric for quantifying the effectiveness of a re-identification method. It denotes the expectation of finding the correct match in the top n matches. Performance at rank n reports the probability that the correct match occurs within the first n ranked results from the gallery set. Rank 1 accuracy refers to the percentage of probe persons which are perfectly matched to the gallery set. The nAUC metric presents the area under the CMC curve normalized over the total area of the graph.

4.2. Performance evaluation of the proposed method

In order to assess the performance of the proposed fusion schema for our proposed BiMPeR method, we compared the performance of our method against information fusion levels (*i.e.* score fusion methods and rank fusion methods).

4.2.1. Performance evaluation against other score fusion methods

Table 1 displays the results of the proposed method and other score fusion methods. These methods consist in combining the matching scores obtained by the appearance and gait features into a final matching score to conduct the re-identification process. In this study, we evaluated the performance of the following methods: Product Rule (PR),

Table 1. Performance evaluation against other score fusion methods.

		Rank-1	Rank-2	Rank-3	Rank-4	Rank-5	Rank-6	nAUC
Score fusion based methods	BiMPeR	96.27	97.84	98.43	99.01	99.60	100	99.86
	PR	95.49	97.64	97.64	98.23	98.62	99.01	99.76
	MaR	77.84	87.64	91.96	95.09	95.88	96.66	98.62
	MiR	86.66	95.68	96.66	96.86	97.05	97.45	99.35
	WS	95.88	97.64	97.64	98.43	98.82	99.01	99.79

Table 2. Performance evaluation against rank fusion methods.

		Rank-1	Rank-2	Rank-3	Rank-4	Rank-5	Rank-6	nAUC
BiMPeR		96.27	97.84	98.43	99.01	99.60	100	99.86
Rank Fusion Based Methods	HR	79.41	94.50	98.23	99.80	99.80	100	99.64
	BC	90.98	95.68	96.86	97.64	98.43	98.82	99.62
	HT	91.17	94.50	99.21	99.80	100	100	99.78
	HAS	91.96	97.84	99.41	99.80	99.80	100	99.85
	Exp	89.41	93.72	95.29	96.66	97.45	97.64	99.34
	DE	93.33	97.84	99.21	100	100	100	99.87
	Log	91.76	97.05	99.01	99.41	99.80	99.80	99.81

Table 3. Performance comparison between our proposed method against uni-model methods.

	Rank-1	Rank-2	Rank-3	Rank-4	Rank-5	Rank-6	nAUC
BiMPeR	96.27	97.84	98.43	99.01	99.60	100	99.86
Gait based method [4]	85.29	94.50	96.07	96.47	96.86	97.45	99.29
Appearance based method [6]	69.41	82.15	87.05	90.19	91.37	92.54	97.58

Max Rule (MaR), Min Rule (MiR) and Weighted Sum (WS) proposed by [10]. The latter consists in calculating a specific weight for each separated descriptor for the weighted sum method whereas (PR), (MaR) and (MiR) present simple methods as they are applied directly on the matching scores without any pre-processing steps.

From results, it is clear that the proposed bi-model person re-identification method consistently outperforms these methods all over ranks and mainly at Rank-1 accuracy with a rate equal to 96.27%.

4.2.2. Performance evaluation against rank fusion methods

Table 2 shows the results of the proposed method against rank fusion methods. These methods combine the ranked list of the gallery obtained by the MLSAR descriptor and the GAIDS descriptor into a final list based on rank fusion methods. In this study, we compared our proposed method with Highest Rank (HR), Borda Count (BC) proposed by [21] and Hyperbolic Tangent (HT), Hyperbolic Arc Sinus (HAS), Exponential (Exp), Division Exponential (DE), Logarithm (Log) proposed by [12, 19] as a non linear methods.

From results, we can see that the proposed bi-model person re-identification method surpasses these methods all over these ranks and especially at Rank-1 accuracy with a rate equal to 96.27%. This confirms that the rank fusion methods are not appropriate for the person re-identification task.

4.2.3. Performance evaluation against uni-model methods

Table 3 presents the performance of the proposed method (BiMPeR) against uni-model person re-identification methods. We have compared our proposed method with an appearance based method [6] and a gait based method [4].

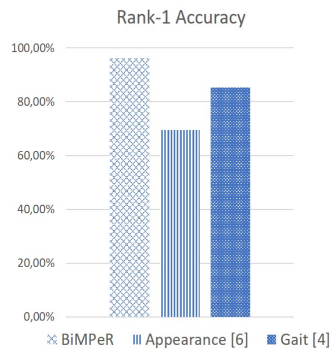

Fig. 5. Performance comparison in terms of Rank-1 accuracy.

We can see that the proposed method's performance reaches 96.27% at rank-1 while those of MLSAR and GAIDS reach 69.41% and 85.29%, respectively. This confirms that appearance and gait are two efficient complementary features. In fact, while the appearance characteristics allows to distinguish people based on the clothes patterns and accessories style, the gait characteristics allows to distinguish people based on their walking manner.

5. Conclusions and future work

In this paper, we presented a Bi-Modal Person Re-identification method based on both appearance and gait features. Appearance features are modelled using the Multi-Level Semantic Appearance Representation descriptor (MLSAR), while gait features are modelled using the Gait Dynamic Selection descriptor (GAIDS). A score fusion-based method was adopted to fuse these characteristics. The experimental results proved the effectiveness of the proposed method compared to the state-of-the-art uni-model person re-identification ones. It reaches 96.27% at rank-1 while those of MLSAR and GAIDS reach 69.41% and 85.29%, respectively, on the CASIA dataset.

The promising obtained results encourage us to face more challenges for intelligent video surveillance applications. For instance, it is interesting to investigate the problem of person re-identification in night-time by exploring the thermal domain.

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