Abstract. In video-surveillance, person re-identification is the task of recognising whether an individual has already been observed over a network of cameras. Typically, this is achieved by exploiting the clothing appearance, as classical biometric traits like the face are impractical in real-world video surveillance scenarios. Clothing appearance is represented by means of low-level local and/or global features of the image, usually extracted according to some part-based body model to treat different body parts (e.g. torso and legs) independently. This paper provides a comprehensive review of current approaches to build appearance descriptors for person re-identification. The most relevant techniques are described in detail, and categorised according to the body models and features used. The aim of this work is to provide a structured body of knowledge and a starting point for researchers willing to conduct novel investigations on this challenging topic.

1 Introduction

Person re-identification consists of recognising an individual who has already been observed (hence the term re-identification) over a network of video surveillance cameras. The topic is currently attracting much interest from researchers, due to the various possible applications such a technique can enable, e.g., off-line retrieval of all the video-sequences where an individual of interest appears, whose image is given as query, or on-line pedestrian tracking over multiple, possibly not-overlapping cameras (a task also known as re-acquisition).

While several biometric traits can be in principle used to this aim, strong pose variations and unconstrained environments make the use of classical biometric traits like face difficult of impractical with the typical sensors and setting of a surveillance network. Therefore, researchers explored the use of cues that pose less constraints, at the expense of an intrinsically lower identification capability. Among them, clothing appearance is used in the most of re-identification methods, as a soft, session-based cue, that is relatively easy to extract, and exhibits uniqueness over a limited time span. Various descriptors of the clothing appearance have been proposed so far in the literature. They are mostly designed heuristically, and are based on the extraction of various kinds of low-level local and global features from the images showing the individual. Typically, they exploit a part-based body model, to take into account the non-rigid structure of the human body and treat the appearance of different body parts (e.g. torso and legs) independently.

This paper provides an overview of existing methods used in literature for the task of person re-identification, with particular respect to the techniques used to build a descriptor of the body appearance. The presented review is mostly based on Chapter 2 of my thesis work. The remainder of the paper is structured as follows. Sect. 2 first gives a simple formal statement to person re-identification. Then Sect. 3 reviews current approaches to construct appearance descriptors. The survey is conducted under two “orthogonal” viewpoints, namely the kind of body model and the kind of features used (Sect. 3.1).
and Sect. 3.2 respectively). Sect. 3.3 then focuses on the problem and current approaches of combining different feature sets. While almost all existing methods use the clothing appearance as main cue to perform re-identification, it is worth to note that other approaches have been attempted in literature, for instance based on gait, or anthropometric measures captured through novel RGB-D sensors. These methods are briefly surveyed in Sect. 4. Finally, Sect. 5, which concludes the paper.

2 Problem overview

Formally, person re-identification can be modelled as a recognition/matching task, where a probe individual is matched against a gallery of templates (representing the individuals previously seen by the camera network). Thus, the problem of re-identifying an individual represented by its descriptor \( P \) can be formulated as:

\[
T = \arg \min_{T_i} D(T_i, Q), T_i \in T
\]

(1)

where \( T = \{ T_1, \ldots, T_N \} \) is a gallery of \( N \) template descriptors, and \( D(\cdot, \cdot) \) is a proper distance metric.

In order to address the re-identification problem above, it is indeed fundamental, first, to answer the question of how to represent persons using a descriptor. This is the topic of investigation of the rest of the paper.

3 Appearance descriptors

The procedure of extracting appearance descriptors typically follow a standard pipeline (see Fig. 1 and Fig. 2):

1. the person is detected and tracked by suitable algorithms;
2. the pixels belonging to the person are separated from the background (foreground extraction or segmentation) in each frame of the video-sequence;
3. a descriptor is built from the resulting silhouettes (one for each frame), using local or global features, possibly after different body parts are detected through a body model, in order to take the into account the non-rigid nature of the body;

Descriptors of Step 3 are finally stored in a data base for subsequent searches.

Step 1 requires i) a method to detect people in a given video frame [31] (i.e., to recognise the image regions, or blobs, that contain a person), and ii) a data association algorithm that track people found by the detector [56, 79, 109] (i.e., to associate blobs in subsequent frames to the same person). These two steps may also be carried out together, and reinforce one another [3]. Step 2 is usually carried out using an adaptive model of the background [35].

Many challenging issues can affect some or all the three steps above. Among them we cite (see Fig. 3):

- **Pose and viewpoint variations.** The relative pose of a person with respect to the cameras of the network varies depending on the walking path of that person, and of the viewpoint of the camera. This may cause consistent variations of the person appearance.

- **Partial occlusions.** Parts of a person may be not visible to the camera due to occlusions caused by objects, clothing accessories or other people. This may cause the segmentation algorithm to fail in separating one person from the rest of the scene; consequently, descriptors may be built from images partially corrupted by the source of the occlusion.

- **Illumination changes.** Illumination conditions may differ in different cameras, and in
the same camera in different periods of time due to changing environmental conditions. This may result in appearance changes over different cameras and during time.

- Changes in colour response. Different cameras may have a different colour response, that may affect person appearance as well.

The vast majority of methods assumes that the steps of detection, tracking and segmentation have been already accomplished using any of the algorithms available in literature, and concentrate on the task of constructing descriptors. The interested reader is referred to [20] and [31] for a comprehensive survey of pedestrian detection and foreground segmentation algorithms. This paper concentrates on Step 3, namely, how to construct discriminant and robust appearance descriptors to match persons in different views.

As stated in the introductory Section, appearance descriptors usually follow a part-based body model: the body is at first subdivided in parts. Then, body parts are described via global features or bags (i.e., unordered sets) of local features. Therefore, it is convenient to split the survey of current appearance descriptors in two parts, first reviewing body part subdivision models (Sect. 3.1), then focusing on appearance features (Sect. 3.2). Combining different kind of features may help in attaining a better performance; Sect. 3.3 provides a closer insight on typical approaches for feature combination in appearance descriptors.

### 3.1 Part-based body models

The human body is not a rigid object. Instead, it has a complex kinematics, and can be better described using a part-based model, possibly where relative positions of parts are not fixed a-priori but are inferred from the image. Furthermore, discontinuities of the clothing appearance usually follow the body structure (e.g., the clothing appearances of the upper and lower body usually differ). Many existing appearance descriptors, therefore, exploit some part-based human body model to segment the silhouette into different parts. Some other descriptors (e.g., [7][13][19][27][47][51][52][55][57][60][69][71][83][103][104][111]) consider the body as a whole instead. Part-based body models used in existing appearance descriptors can roughly be divided into three categories:

- **fixed models**, in which size and relative position of body parts are defined a-priori;
- **adaptive models**, that try to fit a predefined part subdivision model to the image of the person;
- **learned models**, that previously learn the model constraints (e.g., relative parts disposition) from a labelled training set of images of individuals.

In the rest of this Section, part-based body models belonging to the three categories above are reviewed and compared.

#### 3.1.1 Fixed part models

Probably the simplest kind of part subdivision is a fixed one, in which the sizes and positions of body parts are chosen a-priori. An example of this approach can be found in [67][84][113], where the body is subdivided into six horizontal stripes of equal size, that roughly capture the head, upper and lower torso and upper and lower legs. Similarly, in [5] the silhouette is subdivided in five equal-sized stripes. An even simpler fixed part subdivision is used in [61]. Three horizontal strips of respectively 16%, 29% and 55% of the total blob height roughly locate head, torso and legs, then the first strip is discarded as the head typically consists of few pixels and is not informative for the clothing appearance.

#### 3.1.2 Adaptive part models

Other body models are *adaptive*, in the sense that they try to fit a predefined part subdivision model to the image of the individual. In one of the descriptors proposed in [5], the MPEG-7 Dominant Colour Descriptor (DCD) [108] is used to dynamically separate the body into two parts, upper and lower body, looking for discontinuities in dominant colours (the same DCD is also used as feature set to describe each body part, see Sect. 3.2). The approach of [30] extends the basic idea of exploiting appearance anti-symmetries of [5]. It dynamically finds three body areas, namely...
the head, torso, and legs, exploiting symmetry and anti-symmetry properties of silhouette and appearance. To this aim, two operators are defined. The first measures is called \textit{chromatic bilateral operator}. It measures the appearance anti-symmetry of a certain image region with respect to a given horizontal axis, and is defined as

\[ C(y, \delta) = \sum_{B[y-\delta, y+\delta]} d^2(p_i, \hat{p}_i), \]

where \( d(\cdot, \cdot) \) is the Euclidean distance, evaluated between pixels represented in the HSV colour space \( p_i \) and \( \hat{p}_i \) located symmetrically with respect to an horizontal axis placed at height \( y \) of the person image. This distance is summed up over the person pixels lying in the horizontal strip \( B[y-\delta, y+\delta] \) centred in \( y \) and of height \( 2\delta \).

The second is called \textit{spatial covering operator} and measures the difference of the silhouette areas of two regions:

\[ S(y, \delta) = \frac{1}{W} \left| A(B[y-\delta, y]) - A(B[y, y+\delta]) \right|, \]

where \( W \) is the width of the blob, and \( A(B[y-\delta, y]) \) and \( A(B[y, y+\delta]) \), denote the number of person pixels respectively of the strip of vertical extension \([y-\delta, y]\) and \([y, y+\delta]\). These operators are combined to find two axes, \( y_{HT} \) and \( y_{TL} \), that respectively separate head and torso, and torso and legs. These axes are defined as

\[ y_{TL} = \arg \min_y \left( 1 - C(y, \delta) + S(y, \delta) \right), \]

\[ y_{HT} = \arg \min_y \left( -S(y, \delta) \right). \]

The parameter \( \delta \) is set to a value of \( \delta = Y/4 \) where \( Y \) is the blob height in pixels. The values \( y_{HT} \) and \( y_{TL} \) isolate three regions approximately corresponding to head, body and legs (Fig. 4(a)). The head part is discarded as it carries very low informative content. As claimed by the authors, this strategy is able to locate body parts which are dependent on the visual and positional information of the clothes, robust to pose, viewpoint variations, and low resolution. After [36], the same part-based model has been used in various other works [14, 72, 73, 89, 91, 93, 106].

A deformable model that is fitted to each individual to find six body regions is used one of the methods in [44], based on decomposable triangulated graphs [2]. A triangulated graph is a collection of cliques of size three, that has a perfect elimination order for their vertices, i.e., there exists an elimination order for all vertices such that (i) each eliminated vertex belongs only to one triangle, and (ii) a new decomposable triangulated graph results from eliminating the vertex.

The model is fit to the image of a person using the following strategy. Let the model be a decomposable triangulated graph \( T \) with \( n \) triangles \( T_i, i = 1, \ldots, n \). The goal is to find a function \( g \) that maps the model to the image domain, such that the consistency of the model with salient image features is maximised, and deformations of the underlying model are minimised. The function \( g \) must be a piecewise affine map [38], i.e the deformation of each triangle \( g_i(T_i) \) must be an affine transformation. The problem becomes to minimise an energy functional \( E(g, I) \) that can be written as a sum of costs:

\[ E(g, I) = \sum_i E_i(g_i, I) = \sum_i \left( E_i^{data}(g_i, I) + E_i^{shape}(g_i) \right), \]

where the \( I \) represents the image features. The terms \( E_i^{shape}(g_i) \) take into account the cost for shape distortion of the \( i \)-th triangle, while \( E_i^{data}(g_i, I) \) attracts the model to salient image features, which are found using an edge detector (Canny’s algorithm [23]). As shown in [2], a model based on decomposable triangulated graphs can be efficiently optimised using dynamic programming. Once the model has been fitted with regard to the image, the individual is partitioned into six salient body parts, shown Fig. 4(b).
with different colours. An example of application to a real pedestrian image is shown in Fig. 4c.

### 3.1.3 Learned part models

More recently, some methods that rely on previously trained body part detectors and articulated body models have been proposed. Part detectors are statistical classifiers that learn a model of a certain body part (e.g., an arm) from a given training set of images of people where body parts are manually located and labelled. Typically, these detectors exploit features related to the edges contained on the image. An approach of this kind has been used in [15, 16] based on the work of Felzenszwalb et al. [37]. The overall body model is made up of different part models; each one, in turn, consists of a spatial model and of a part filter. The spatial model defines a set of allowed placements for a part with respect to the bounding box containing the person, and a deformation cost for each placement. To learn a model, a generalisation of Support Vector Machines (SVM) [22] called latent variable SVM (LSVM) is used. In [15, 16], such model is used to detect four different body parts, namely head, left torso, right torso and the upper legs (see Fig. 3a).

An articulated body model based on Pictorial Structures (PS) was proposed in [21] and later exploited in [25] for the task of re-identification. In [26], six parts are considered (chest, head, thighs and legs, see Fig. 3b), while the original PS model is also able to detect and locate upper and lower arms.

A PS model for an object [39] is a collection of parts with connections between certain pairs of parts (an example is provided in Fig. 3c). The approach of [4] uses a PS of the human body that is made up of a set of \(N\) parts, and a set of generic part detectors based on descriptors of the shape. The model and the body part detectors are trained on a training set of images of people.

Let \(L = \{l_0, \ldots, l_{N-1}\}\) be the set of configurations of each body part. Each \(l_i\) is the state of the \(i\)-th body part \(l_i = (x_i, y_i, \theta_i, s_i)\), where \(x_i\) and \(y_i\) are the image coordinates of the part centre, \(\theta_i\) is the absolute part orientation, and \(s_i\) is the part scale, relative to the size of the part in the training set. Given the image evidence \(D\), the problem is to maximise the a-posteriori probability (posterior) \(p(L|D)\) that the part configuration \(L\) is correct. The posterior is proportional to

\[
p(L|D) \propto p(D|L)p(L)
\]

according to Bayes’ theorem [34]. The term \(p(D|L)\) is the likelihood of the image evidence given a particular body part configuration, while \(p(L)\) corresponds to a kinematic tree prior. Both are learned from a training set, as follows.

**Kinematic three prior.** The prior \(p(L)\) encodes the kinematic constraints, i.e. the constraints on the relative parts disposition. The body structure is mapped on a directed acyclic graph, so that \(p(L)\) can be factorised as

\[
p(L) = p(l_0) \prod_{(i,j) \in E} p(l_i|l_j)
\]

where \(E\) denotes the set of all directed edges in the kinematic tree, and \(l_0\) is the root node, that in [4] is chosen to be the torso body part.

The prior for the root part configuration \(p(l_0)\) is assumed to be uniform. To model part relations \(p(l_i|l_j)\), a transformed space is used, where such relations can be modelled as Gaussian [39]. More specifically, the part configuration \(l_i = (x_i, y_i, \theta_i, s_i)\) is transformed into the coordinate system of the joint between the two parts \(i\) and \(j\) using the transformation:

\[
T_{ji}(l_i) = \begin{pmatrix} x_i + s_i d_{ji}^l \cos \theta_i + s_i d_{ji}^s \sin \theta_i \\ y_i + s_i d_{ji}^l \sin \theta_i + s_i d_{ji}^s \cos \theta_i \\ \theta_i + \bar{\theta}_{ji} \\ s_i \end{pmatrix}
\]

where \(d_{ji} = (d_{ji}^l, d_{ji}^s)^T\) is the mean relative position of the joint between the two parts \(i\) and \(j\), in the coordinate system of part \(i\), and \(\bar{\theta}_{ji}\) is the relative angle between the two parts. Then, part relations are modelled as Gaussian in the transformed space:

\[
p(l_i|l_j) = \mathcal{N}(T_{ji}(l_i)|T_{ij}(l_j), \Sigma_{ji})
\]
where $d_{ij}$ and $\Sigma_{ij}$ can be learned via maximum likelihood estimation \cite{34} from a labelled training set of images of people. It is worth noting that the body parts are only loosely attached to the joints (also called a loose-limbed model \cite{85}), which helps increasing the robustness of the pose estimation. Fig. 5-d shows the priors learned from the multiple views and multiple poses people data set of \cite{85}, a common benchmark corpus for body pose estimation algorithms.

Likelihood of the image evidence. To estimate the likelihood $p(D|L)$, the methods relies on a different appearance model for each body. Each appearance model will result in a part evidence map $d_i$ that reports the evidence for the $i$-th part for each possible position, scale, and rotation.

Assuming that the different part evidence maps are conditionally independent, and that each $d_i$ depends only on the part configuration $l_i$, the likelihood $p(D|L)$ can be written as:

$$p(D|L) = \prod_{i=0}^{N} p(d_i|l_i).$$

Substituting Eq. (8) and Eq. (11) in Eq. (7), one finally obtains:

$$p(L|D) \propto p(l_0) \cdot \prod_{i=0}^{N} p(d_i|l_i) \cdot \prod_{(i,j) \in E} p(l_i|l_j).$$

The part detectors $p(d_i|l_i)$ use a variant of the shape context descriptor \cite{75}, that consists in a log-polar histogram of locally normalised gradient orientations. The feature vector is obtained by concatenating all shape context descriptors whose centres fall inside the bounding box of the part. During detection, different positions, scales, and orientations are scanned with sliding windows. The classifier used for detection is an ensemble of a fixed number of decision stumps combined through AdaBoost \cite{42}.

3.2 Features

Each body part (or the whole image of the individual, if no body part subdivision model is used) is typically described using one or more different global or local features. In this Section, the main kinds of features used in the literature are reviewed.

3.2.1 Global features

Global features are characteristics measured in the whole image or body region considered, and are usually represented as a fixed-size vector of real numbers. Probably the most widely used feature of this kind is the global colour histogram. Given a colour image of size $N = W \times H$ pixels, the colours of the image are at first quantised into $B$ bins $1, \ldots, B$. The histogram is then constructed as the count of the number of occurrences per bin. Typically, such count is normalised as the fraction of pixels of the image belonging to the bin. Colour image pixels are typically represented as a triplet of values, representing the amount of colour in different colour channels (e.g., Red, Green and Blue). In this case, each colour channel is quantised separately. The resulting histogram can be multi-dimensional (one dimension for each channel), or mono-dimensional (the final histogram is constructed as the concatenation of histograms in each colour channel). The latter saves a lot of space (e.g., if 16 bin are used for each colour channel, the size of the multi-dimensional histogram would be $16 \times 16 \times 16 = 4096$ bins, while the mono-dimensional one would have a size of 48 bins) and has usually a similar discriminant capability to the former. Various colour spaces exist in the literature. Among them it is worth citing:

- The RGB colour space, where each colour is represented as the corresponding amount of Red, Green and Blue; it directly relates to the way devices acquire and visualise colours.

- Perceptual colour spaces, i.e., spaces inspired to the way the human brain perceives colour; e.g., the Hue-Saturation-Value (HSV) colour space, in which the light intensity (V channel) is separated from the colour tonality (H channel) and the saturation of the colour (S channel).

Good surveys on colour spaces are provided in \cite{102,103}. Many appearance descriptors use global colour histograms, to represent the whole body appearance \cite{13,57,67} or the overall appearance of each body part \cite{8,14,15,16,36,44,47,61,84,106,113}. Du et al. \cite{33} evaluated the use of colour histograms computed in various colour spaces for building appearance descriptors for re-identification. To tackle with the lower amount of information usually carried by peripheral pixels (that could actually belong to the background, as the person segmentation is usually very noisy), in \cite{25,36,106} these pixels receive less weight than those near the vertical silhouette symmetry axis.

The colour space is typically quantised in an uniform fashion. However, many colour ranges can be irrelevant for representing a certain appearance, e.g. colours ranges that are not present in the image, or
whose coverage percentage with respect to the image is irrelevant. For this reason, some approaches try first to find the most representative colour ranges, then describe the appearance with respect to these ones. One of the methods of [8] and the methods of [15, 16, 60] use the Dominant Colour Descriptor (DCD) (also called Representative Meta Colours Model, RMCM) of MPEG-7, which provides a compact description of the most representative colours. Given an image, the DCD algorithm first finds the $K$ dominant colours [30], via $k$-means clustering of all the colour tripletts in the image. Then, the descriptor is defined as

$$F = \{\{c_i, p_i\}, i = 1, \ldots, K\}$$ (13)

where $c_i$ is the $i$-th dominant colour (i.e., the centroid of the $i$-th cluster), and $p_i$ is the percentage of image pixels that fall into the $i$-th cluster. A similar approach is used also in [24], called Global Colour Context. The method of [27] partly differs to the former ones, although it shares with them the same idea of describing appearance in terms of the most important colours. Instead of finding representative colours by clustering, they are chosen a priori; specifically, eleven colours, usually referred to as culture colours [26], are used: black, white, red, yellow, green, blue, brown, purple, pink, orange, and grey. Each pixel of the image is assigned to the most similar cultural colour.

Colour histograms are invariant to scale and show a good robustness with respect to partial occlusions, if the occlusion itself is small. However, they are sensitive to changing brightness and colour response of the sensor. Illumination conditions in outdoor environments may consistently vary during time due to changing weather conditions and the varying illumination of the Sun during the day. On the other hand, lighting conditions of indoor scenes may vary from camera to camera due to different types of lamps (e.g., incandescent, tungsten, neon) and also due to weather conditions in case of presence of windows that let the Sun light enter. Colour response of the sensors may also vary due to environmental conditions and due to the automatic colour balance that often takes place in-camera.

Different mechanisms have been exploited to address, at least partially, the above problems. Probably the simplest one is colour normalisation. The chromaticity RGB space is one of these techniques, used in [19, 33, 104], and consists of dividing each colour channel of each pixel by the sum of all the channels of that pixel, e.g. $R' = R/(R + G + B)$.

Another common technique is the Grey-world normalisation [21], which relies on the assumption that the average colour of a scene is usually a tonality of grey. It consists of dividing each RGB channel of every pixel by the average value of that channel in the image, e.g. $R' = R/\text{mean}(R)$. Grey-world normalisation is used in [103, 104]. Similar to Grey-world is the affine normalisation used in [19, 103, 104], where pixel-values of each color channel are normalised independently by subtracting the average and scaling them with the standard deviation, e.g. $R' = (R - \text{mean}(R)) / \text{std}(R)$.

Alternative to colour normalisation is histogram equalisation [20], which is used in the identification methods of [19, 103, 104]. It is based on the assumption that a change in illumination preserves the rank ordering of sensor responses (i.e. pixel values). The rank measure for the $i$-th bin of the histogram and the $k$-th colour channel is defined as $M_k(i) = \sum_{u=0}^{i} H_k(u) / \sum_{u=0}^{N} H_k(u)$, where $N$ is the number of bins and $H_k(i)$ is the histogram relative to the $k$-th channel.

Finally, Piccardi and Cheng [83] exploited a colour quantisation scheme to mitigate the effect of illumination changes between cameras. They represent the image with a Major Colour Spectrum Histogram (MCSH), that is, an histogram of the top $N$ represented colour values in the image.

Another problem of histograms is that they do not retain any information on the spatial disposition of colours. A simple way to incorporate the spatial information is to add the relative pixel height (i.e. the ratio between the vertical coordinate of the pixel and the total height of the silhouette) as another channel of the image. A colour-position histogram can be then built which is able to spatially localise the colour distribution [19, 103, 104]. A similar approach is used also in [61], where two dimensions are added to each pixel (i.e. the radial and angular distance to the torso center) and quantised. The Color Structure Descriptor (CSD) of MPEG-7 [71] is used in [20], and encodes the distribution of colour by the following steps: (i) move a window of size $8 \times 8$ pixel over the picture ; (ii) determine which colours are present in within the window; (iii) increase the corresponding bins in a color histogram by one, independently of the number of pixels of these colors.

Instead of looking at colour properties, other kinds of global features try to characterise gradients, textures and repeated patterns of the whole body ap-

\[ \text{...\text{horizontal co...} } \]

\[ = \text{...not used, as it is...} \]
pearance or of each body part. Gabor filters \cite{76} ans Schmid filters \cite{95} are orientation-sensitive filters that capture texture and edge informations on the image. The former ones are aimed at detecting horizontal and vertical lines, while the latter ones detect circular gradient changes. They are used in various appearance descriptors \cite{17, 67, 69, 84, 113} in conjunction with other colour-related features.

Hahnel et al. \cite{50} compared various different texture features. The fist is the 2D Quadrature Mirror Filter (QMF), a well known filter in signal processing that splits a 2D input signal into two bands (high and low-pass) in each direction (horizontal, vertical and diagonal). The second is the Oriented Gaussian Derivatives (OGD) filter, based on steerable Gaussian filters. Also, two MPEG-7 texture-related descriptors, are used the Homogeneous Texture Descriptor (HTD) that uses Gabor filters, and the Edge Histogram Descriptor (EHD), basically an histograms of the directions of each edge pixel in the image \cite{99}.

It is worth pointing out that texture-based features have always been used in combination to colour-based ones. Information on repeated patterns is in fact likely to be not distinctive enough when used alone. Hahnel et al. \cite{50} confirmed this thought, and showed also that the combination of colour and texture-based descriptors may lead only to minor performance improvements.

3.2.2 Local features

The term local feature refers to an appearance characteristic of a small portion of the image (e.g., the neighbourhood of a pixel). The regions where local features are extracted can be chosen in various way (e.g. by dense sampling, by an interest operator or at random). Each small region is described by a feature vector (e.g., an histogram). This lead to a representation of the image as as a bag (set) of local features.

Interest points are one important category of local features. The most famous among them is SIFT (Scale Invariant Feature Transform) \cite{68}, where at first salient points of the image are chosen via an interest operator that looks for “stable” locations in the image (i.e. locations that are identifiable over different scales and rotations). This operation is carried out by detecting scale-extrema locations in the scale space of scale \( \sigma \), which is defined by the function

\[
L(x, y, \sigma) = \mathcal{N}(x, y, \sigma) \ast I(x, y) \tag{14}
\]

where \( * \) is the convolution operation in the image coordinates \( x \) and \( y \), and \( \mathcal{N}(x, y, \sigma) \) is a 2-D Gaussian with standard deviation \( \sigma \). Stable key-points can be detected in this space e.g. by using difference-of-Gaussians functions convolved with the image:

\[
D(x, y, \sigma) = (\mathcal{N}(x, y, k\sigma) − \mathcal{N}(x, y, k\sigma)) \ast I(x, y) = L(x, y, k\sigma) − L(x, y, \sigma) \tag{15}
\]

To detect the local minima and maxima of \( D(x, y, \sigma) \), each point \((x, y)\) is compared with its 8 neighbours at the same scale \( k\sigma \), and its 9 neighbours in the two scales \((k-1)\sigma\) and \((k+1)\sigma\). If this value is the minimum or maximum of all these points, then this point is an extrema, and it is labelled as key-point. A subsequent stage filters out low-contrast and noisy points. The remaining key-points are described as a histogram of the edge orientations of a small window centred on the key-point. SIFT points or its variants, (e.g., Speeded-Up Robust Features, SURF \cite{12}) are used in various appearance descriptors to represent the whole body appearance.

Interest point are typically chosen via interest operators \cite{52, 60, 69, 72, 73} but some works exist (e.g., \cite{111}) that adopt dense sampling instead.

Other approaches use different kinds of local features.

Maximally Stable Colour Regions (MSCR) \cite{41} are used in \cite{25, 36, 69}. The MSCR algorithm first detects a set of regions in the image (Fig. 6-a) by using a constrained agglomerative clustering on image pixels, which show the maximal chromatic distance. The detected regions are then described by their area, centroid, second moment matrix and average color, forming 9-dimensional feature vectors, and are stable to scale and affine transforms.

Recurrent Highly-Structured Patches (RHSP) used in the method of \cite{36}, try instead to capture repeated patterns and textures of the clothing appearance. The procedure of creating RHSPs is as follows. First, random and possibly overlapping small patches are extracted from the image. Patches that do not carry texture informations (e.g. showing uniform colours) are discarded by thresholding the patch entropy, computed as the sum of the entropy of each colour channel. Remaining patches are then further filtered, keeping only those that exhibit invariance to rotations. Second, the recurrence of each patch is evaluated, via Local Normalised Cross-Correlation over a small local region containing that patch. Third, patches that show a high degree of recurrence are clustered, maintaining for each final cluster the patch nearest to the centroid. These patches are finally
described as their Local Binary Pattern histogram [81], a simple yet efficient way to describe textured content, based on a per-pixel transform that encodes small-scale appearance structures.

Instead of using interest operators like the one defined by Eqs. (14)-(15), or other proper selection criteria to choose where to extract a local feature, in [47], a set of strips of fixed height and position are extracted from the image, and described by a concatenation of colour histograms in different colour spaces and Gabor and Shmid filters. Similarly, in [55] partly overlapping rectangular patches of fixed size are sampled from the image following a pre-defined regular grid. Each patch is represented by its colour histogram in the HSV colour space, and by its LBP histogram to capture textures and repeated patterns. An analogous approach is also used in [111], except for the fact that patches are not overlapping. Finally, instead of using regular sampling, one could sample patches at random, an approach followed for instance in [93].

To reduce the dimensionality of local features-based descriptors, in [89, 91] a dissimilarity approach has been introduced [82]: a bag of local features is turned into a dissimilarity-vector that encodes the degree of similarity to a set of predefined prototype local features. Prototypes are found by clustering local features extracted from a design set of images of people. In case a part-based body model is used, memberships to body parts are kept and each body part is represented via a dedicated dissimilarity vector. The same dissimilarity-based descriptor was then used in [90, 92, 94], also for tasks different that person re-identification.

3.3 Combination of features and matching

Many person re-identification methods use appearance descriptors made up of only one kind of features among the above mentioned ones, typically based on colour or interest points [6, 8, 15, 16, 19, 23, 27, 44, 51, 52, 61, 72, 73, 103, 104]. However, as combining different sources of information usually helps in attaining a better performance, especially when sources are complementary (i.e. they look at different aspects of the appearance, e.g. colour and texture), many authors have defined descriptors that use a combination of features.

In principle, two main combination techniques can be exploited to this aim [87]:

1. feature-level fusion: if the features used are made up of a single vector of fixed size (e.g. global features, or local features with an intrinsic ordering) they can be combined simply by concatenating feature vectors;

2. score-level fusion: a distinct detector/matcher is used for each feature, and their real-valued scores are combined (e.g., by averaging them, or using their maximum value).

The first approach is followed for instance in [33, 55, 106]. The second approach requires to define a proper fusion rule. Many methods used a weighted average of the partial scores attained with each single feature, where weights are fixed a-priori by the system designer [13, 14, 25, 36]. Another approach is to learn a proper metric or a set of weights from a training set. In [47], AdaBoost [42] is used to this aim: each feature set is associated to a weak two-class classifier (a decision stump) which discerns between the class 0 (identities differ) and 1 (identity is the same) based only in that feature set. The method of [84] tries to find a linear function to weight the absolute difference of samples by training an ensemble of RankSVM rankers [59] given pairwise relevance constraints. The Probabilistic Relative Distance Comparison (PRDC) technique of [113] maximises the probability that a pair of true match has a smaller distance than that of a wrong match. The output

\footnote{In verification tasks, whose goal is to establish whether the claimed identity is true, combination can also be performed at decision level, i.e., by combining the crisp outputs of classifier/detectors. It can not be applied to person re-identification, which is a recognition task instead.}
is an orthogonal matrix which essentially encodes the global importance of each feature. In [69] a pairwise metric is learned through a recently proposed method, Pairwise Constrained Component Analysis (PCCA) [74], which learns a projection into a low-dimensional space where the distance between pairs of data points respects the desired constraints.

Metric learning and similar approaches always help in boosting re-identification performance. However, it is worth to note that all the above methods require a training set of labelled data. Such set can be for instance the gallery of templates. This requires that the template gallery is fixed, i.e. templates cannot be added during system operation; such constraint might be too strong for real-world application scenarios.

4 Other cues

Some cues alternative to the clothing appearance have been exploited in the literature to perform person re-identification or assimilable tasks. Despite the intrinsic limitations of such cues, they could be potentially of help in certain conditions, possibly combined with appearance cues.

Human gait, i.e. the recurrent pattern of motion of a person walking, is among these cues. In cognitive science, it is known to be one of the cues that humans exploit to recognise people [100]. Among the approaches to characterise gait, the recently proposed Gait Energy Image (GEI) [53] has attracted the attention of many researchers. Here, the gait signature is formed by by normalising, aligning and averaging a sequence of foreground silhouettes corresponding to one “walking period” (see Fig. 7). Principal Component Analysis (PCA) is then used to reduce the dimensionality of the signature.

The use of Gait Energy Image can lead to high recognition rates [107] and can overcome one of the main limitations of clothing appearance-based approaches, that is, the impossibility of distinguishing people when their clothing changes between observations. It is also not directly affected by illumination changes. However, it requires perfect alignments of the silhouettes to be compared, and is sensible to segmentation errors. These two constraints severely limit the use of GEI-based methods on practical, real-world applications. Researchers have therefore attempted to explore other approaches. Zhao et al. [110] and more recently Gu et al. [48] used a 3D skeletal representation, that however requires multiple overlapping camera views or a constrained environment to construct and track it.

Some authors attempted instead to perform remote face recognition [78], that is, face recognition with low resolution images. As low resolution face images are not directly usable for recognition, many approaches attempted to address the problem through the obvious way of trying to increase image resolution, using super-resolution techniques [19, 51, 55, 94]. Other authors proposed instead techniques that work directly on low resolution images, by exploiting metric learning [65, 66], multidimensional scaling [18], or multiple frames from video sequences [5]. All the approaches above could in principle be used in conjunction with appearance cues to increase re-identification accuracy when the face is visible.

Another useful set of soft cues is anthropometry, that is, the characterisation of individuals through the measurement of physical body features [80], e.g., height, arm length, and eye-to-eye distance. Measures are typically taken according to a number of body landmark points (e.g., elbows, hands, knees, feet), that have to be localized either automatically or manually. In the classic study by Daniels and Churchill [28], the uniqueness of 10 different anthropometric traits was evaluated on a large data base of 4063 individuals. None of the considered traits was found to be “average” (i.e., approximately close to the mean point), considering all 10 dimensions. Furthermore, only 7% of the individuals were “average” in 2 dimensions, and 3% in 3 dimensions.

Although the use of anthropometric measurements for person recognition has been proposed in many works, their extraction was often based on costly devices, like 3D laser scanners, and/or require user collaboration in a constrained environment [15, 77, 80]. In some works, anthropometric measurements are extracted from a single RGB camera view, instead. In [11] a method that does not require camera calibration was proposed, for simultaneously estimating anthropometric measurements and pose. However, the former are measured up to a scale factor, and consequently can not be used to directly compare individ-
Figure 8: (a) The 20 skeletal points tracked by the Kinect SDK in the classical representation of the Vitruvian Man. (b–d) Examples of the pose estimation capabilities of the Kinect SDK. Depending on the degree of confidence of the estimation of the points position, the Kinect SDK distinguishes between good (in green) or inferred (in yellow) points, the latter being less reliable than the former.

ults in images acquired by different cameras. Calibration is not required in [1] as well, although 13 body landmarks have to be manually selected, from an image of an individual in frontal pose. Other methods focus on height measurement only [17, 43, 63, 64, 70], but require camera calibration to estimate absolute height values. Interestingly, in [70] height is used as a cue for the task of associating tracks of individuals coming from disjoint camera views, which is actually the same re-acquisition task that is enabled by person re-identification.

None of the above works fits the typical setting of person re-identification tasks, which is characterised by multiple, uncalibrated cameras and unconstrained environment, with free poses and non collaborative users. Recently, it has been shown that body pose can be reliably estimated in real-time by exploiting RGB-D sensors [97, 101], like the MS Kinect, a device recently introduced in the video-gaming market. The pose estimation functionality of Kinect SDK [62], which is based on a similar method, provides the absolute position (in meters) of 20 different body joints in real-time, with high reliability (see Fig. 8). Detecting joint positions enables the evaluation of several anthropometric measures. In [10] such joints were used to extract a set of different anthropometric measures from front or back poses: distance between floor and head, ratio between torso and legs, height, distance between floor and neck, distance between neck and left shoulder, distance between neck and right shoulder, and distance between torso center and right shoulder. Other three geodesic distance measures were estimated from the 3D mesh of the abdomen, obtained from the Kinect depth map: torso center to left shoulder, torso center (located in the abdomen) to left hip, and between torso center to right hip. Results reported in [10] appear promising. However, many of the considered anthropometric measures are hard or impossible to extract from unconstrained poses. For instance, extracting measures from 3D mesh requires near-frontal pose (abdomen is hidden in back pose); neck distance to left and right shoulders becomes hard to compute from lateral pose, even using a depth map, and requires to distinguish between left and right body parts. Such issues limit the actual set of anthropometric measures that can be used in realistic scenarios.

5 Conclusions

This paper provided a survey of current approaches and methods for constructing appearance descriptors for person re-identification. State-of-the-art descriptors have been reviewed from two different viewpoints, namely the kind of body model and the kind of features used to represent a person. We tried to provide a comprehensive analysis and description of the algorithms in a structured and consolidated way. We hope that this work will be a useful reference for anyone in the research community willing to work on this interesting and challenging topic.

References


[39] Pedro F. Felzenszwalb and Daniel P. Huttenlocher. Pictorial structures for object recogni-


[91] Riccardo Satta, Giorgio Funera, and Fabio Roli. Fast person re-identification based on dis-


[107] Dong Xu, Yi Huang, Zinan Zeng, and Xinxing Xu. Human gait recognition using patch distribution feature and locality-constrained group


