The goal of person re-identification (re-id) is to maintain the identity of an individual in diverse locations through different non-overlapping camera views. Re-id is fundamentally challenging because of appearance changes resulting from differing pose, illumination and camera calibration of the two views. Existing literature deals with the two-camera problem and proposes methods that seek to match a single image viewed in one camera to a gallery of images in the other. We propose structured prediction as a way to learn simultaneous matches across the two camera views. We deal with appearance changes in our prediction model through basis functions that encode co-occurrences of visual patterns in the two images. We develop locality sensitive co-occurrence measures as a way to incorporate semantically meaningful appearance changes. Empirical performance of our method on two benchmark re-id datasets, VIPeR [12] and CUHK Campus [38], achieves accuracy rates of 38.92% and 56.69%, at rank-1 on the so-called Cumulative Match Characteristic curves and beats the state-of-the-art results by 8.76% and 28.24%.

1 Introduction

Person re-identification (Re-id) is emerging as an important problem with the pervasive use of camera networks in surveillance systems. Re-id deals with maintaining identities of individuals traversing different cameras. As in the literature we consider re-id for two cameras and focus on the problem of matching probes (individuals in Camera 1) with those from the gallery (Camera 2).

Re-id is a challenging problem for several reasons. Cameras views are non-overlapping and so conventional tracking methods are not applicable. View angles, illumination and calibration for the two cameras are generally arbitrary, leading to significant variation in appearance to the point that features seen in one camera are often missing in the other. Consequently face recognition methods or those based on matching visual features are often unreliable [35].

While re-id has received significant interest [7, 35, 56], much of this effort can be viewed from the perspective of multi-class classification, namely, methods that seek to classify each probe image into one of gallery images. Broadly re-id literature can be categorized into two themes with one theme focusing on cleverly designing local features [8, 14, 31, 6, 1, 26, 24] and the other focusing on metric learning [6, 23, 25, 27, 40]. Our theme is fundamentally different from the existing literature. We view re-id as an instance of bipartite graph matching, an idea that has been used in other contexts (e.g. [57]). We simultaneously match all or a sub-collection of probes to the gallery images. This is natural for many surveillance contexts, such as in airports, where multiple entities are viewed in a camera at any time. Fig. [1a] illustrates re-id with two camera views as a weighted bipartite matching problem, where images from the two views are taken as nodes in the graph, edges link nodes from the two views, and weights are associated with edges. While max-weight bipartite matching can be efficiently solved for known weights, our setup requires dealing with unknown weights.
Figure 1: (a) Illustration of re-id as a bipartite graph matching problem, where color red and green label the images from two different camera views. (b) Illustration of regions in positive image pairs (i.e. from a same person per column) and negative image pairs (i.e. from different persons per column), enclosed by red (or cyan) color, which have similar spatial co-occurrence patterns.

We use Structured Prediction [33] to learn matches based on manually labeled matchings of training data. We represent the matching objective as a weighted combination of basis functions and learn the relative importance of the different basis functions. In many scenarios [33], these basis functions encode shared or related words or patterns. Re-id demands a different approach on account of the significant variation of appearance due to changes in pose and illumination. Many visual words are missing and not common even among the ground-truth matched images.

We encode pairwise co-occurrences of visual words in our basis functions. The use of co-occurrence patterns is not new (e.g. [2, 10, 20]) but our purpose is different. Our key insight is that aspects of appearance that are transformed in predictable ways, due to the static camera view angles, can be statistically inferred through pairwise co-occurrence of visual words. The structured learning problem is to determine important co-occurrences while being robust to noisy co-occurrences. Indeed as seen in Fig. 1(b) we observe that some regions are distributed similarly in images from different views and robustly in the presence of large cross-view variations. These regions provide important discriminant co-occurrence patterns for matching image pairs.

Pairwise co-occurrences of visual words can be modeled in many ways. However, it has to be semantically meaningful, namely, it has to capture changes in similar things – shirt-with-shirt, skirt-with-skirt etc. We encode images with a sufficiently large codebook to account for different visual patterns. We then map pixels into codewords (i.e. visual words) and embed the resulting spatial distribution of pixels belonging to a codeword into a kernel space through kernel mean embedding [32] with latent-variable conditional densities [18] as kernels. In this way we obtain locality sensitive co-occurrence measures that model semantically meaningful appearance changes Alternatively, we can also interpret our approach (see Fig. 1(b)) as a means to transfer the information (e.g. pose, illumination, and appearance) in image pairs to a common latent space for meaningful comparison. Empirical performance of our method on benchmark re-id datasets (VIPeR [12] and CUHK Campus [38]) achieves accuracy rates of 38.92% and 56.69%, at rank-1 on the so-called Cumulative Match Characteristic curves and beats state-of-the-art results by 8.76% and 28.24%, respectively.

Related Work: The theme of local features for matching is related to our kernel-based similarity measures. To ensure locality, [5] models the appearances of individuals using features from horizontal strips. [11] clusters pixels into similar groups and the scores are matched based on correspondences of the clustered groups. Histogram features that encode both local and global appearance are proposed in [4]. Saliency matching [38, 39], one of the state-of-the-art methods for re-id uses patch-level matching to serve as masks in images to localize discriminative patches. More generally low-level features such as color, texture, interest points, co-variance matrices and their combinations have also been proposed [8, 14, 31, 11, 11, 26, 8, 14, 24]. In addition high-level structured features that utilize concatenation of low-level features [26] or deformable part models (DPMs) [28] have been proposed. Metric learning methods have been proposed for re-id (e.g. [6, 23, 27, 40]). In [30, 17] distance metrics are derived through brightness transfer functions that associate color-levels in the two cameras. [41] proposes distance metrics that lend importance to features in matched images over the wrongly matched pairs without assuming presence of universally distinctive features. Low-dimensional embeddings using PCA and local FDA have also been proposed [29]. Supervised methods that select relevant features for re-id have been proposed by [14] using Boosting and by [31] using RankSVMs.
2 Our Method

We consider two camera re-id problem, as is common in the literature, although we can readily extend our method to multiple cameras. The goal of re-id is to recognize the same person from different camera views. Therefore, we utilize all the images to create a bipartite graph, where all images from view 1 form an independent set and the images from view 2 form the another independent set. The edges between images indicate whether the image pairs are from the same person or not.

2.1 Person Re-identification via Structured Learning

2.1.1 Formulation

We denote the raw training image data as \((x, y) = \big\{\big(I_i^{(1)}, I_j^{(2)}\big), y_{ij}\big\}_{i,j \geq 1}\) where \(I_i^{(1)}\) and \(I_j^{(2)}\) are the \(i^{th}\) \& \(j^{th}\) images of same size from cameras 1 and 2, respectively. Note that \(x\) denotes a set of image pairs, and we take \(x_{ij}\) as an image pair of \(I_i^{(1)}\) and \(I_j^{(2)}\). The variable \(y = \{y_{ij}\}_{i,j \geq 1} \in \mathcal{Y} = \{-1, 0, 1\}^{N_1 \times N_2}\) is the ground-truth bipartite graph structure variable, and \(y_{ij} = 1\) (i.e. true match) if \(I_i^{(1)}\) and \(I_j^{(2)}\) are from the same person, \(y_{ij} = -1\) (i.e. false match) if \(I_i^{(1)}\) and \(I_j^{(2)}\) are from different persons, and \(y_{ij} = 0\) (i.e. no match) if there is no edge linking \(I_i^{(1)}\) and \(I_j^{(2)}\). Re-id reduces to the following bipartite matching problem:

\[
\min_{w} \max_{\tilde{y} \in \mathcal{Y}} \left\{ \frac{1}{2} \|w\|_2^2 + C \max \left\{ 0, w^T f(x, \tilde{y}) - w^T f(x, y) + \Delta(y, \tilde{y}) \right\} \right\}
\]

\[
\text{s.t. } \forall i, j, \ y_{i,j} \in \{-1, 0, 1\}, \ \sum_j y_{i,j} = \sum_j y_{i,j}, \ \sum_i y_{i,j} = \sum_i y_{i,j},
\]

where \(w \in \mathbb{R}^d\) denotes the classifier, \(\tilde{y}\) denotes the predicted bipartite graph structure, \(f(x, y) \in \mathbb{R}^d\) and \(f(x, \tilde{y}) \in \mathbb{R}^d\) denote the feature vectors under different structures, \(\Delta(y, \tilde{y})\) denotes the loss between the structures, \(C \geq 0\) is a predefined constant, \(\|\cdot\|_2\) denotes the \(\ell_2\) norm of a vector, and \((\cdot)^T\) denotes the matrix transpose operator. The constraints on \(\tilde{y}\) ensures that the predicted structure preserves the same topological structure as the ground-truth.

![Figure 2](image)

**Figure 2:** Illustration of 3 different ways of constructing bipartite graphs with 4 different persons, where for nodes each color indicates a person, and for edges solid lines denote true matches and dotted lines denote false matches. This figure is best viewed in color.

It is worth mentioning that our structured learning formulation is flexible and encompasses existing perspectives. We can do so by describing the ground-truth \(y\) in different ways. Fig. 2 illustrates 3 ways of constructing bipartite graph structures: (a) only the true matches are included in the graph with edges weighted by 1; (b) all possible matches are included in the graph where the edges of true matches are weighted by 1, and those of false matches are weighted by -1; (c) matches are generated randomly and weighted by 1 or -1. Correspondingly, the classifiers learned with different structures are generally different as well. For instance, the structure in Fig. 2(b) is the one that linear support vector machines (SVMs) will ideally predict and this setup falls into the existing viewpoint of matching a single probe to a gallery. The issue of choosing ground-truth structures for optimal performance is beyond the topic of this paper.

2.1.2 Learning

In [19], Joachims et. al. proposed a general cutting plane method to solve the 1-slack variable structured SVMs such as Eq. 1 by alternatively solving one variable while fixing the others. Based on [19], we have the following proposition which is used to solve our structured learning problem in Eq. 1 efficiently.
Algorithm 1: Large-scale structured learning algorithm for re-id

**Input**: \( \{ \phi(x_{ij}) \} \), \( y \), \( C \geq 0 \)

**Output**: \( w \)

Randomly initialize \( w \); \( \hat{y} \leftarrow 0 \);

repeat
  \[
  \hat{y} \leftarrow \text{argmax}_{y \in Y} \sum_{i,j} [\hat{y}_{ij} w^T \phi(x_{ij}) + |y_{ij} - \hat{y}_{ij}|] \quad \text{s.t. constraints in Eq. 2}
  \]
  \[
  \bar{y} \leftarrow \hat{y} + \bar{y} - y;
  \]
  \[
  w \leftarrow \text{argmin}_w \left\{ \frac{1}{2} \|w\|^2 + C \sum_{i,j} \max \left\{ 0, \hat{y}_{ij} w^T \phi(x_{ij}) + |\hat{y}_{ij}| \right\} \right\};
  \]
until Converge;

return \( w \);

**Proposition 1.** In Eq. 7 let \( f(x, y) = \sum_{i,j} y_{ij} \phi(x_{ij}) \), \( f(x, \hat{y}) = \sum_{i,j} \hat{y}_{ij} \phi(x_{ij}) \), and \( \Delta(y, \bar{y}) = \sum_{i,j} |y_{ij} - \bar{y}_{ij}| \), where \( \phi(x_{ij}) \in \mathbb{R}^d \) denotes the basis function measuring the similarity between the image pair \( x_{ij} \). Based on Theorem 1 and the cutting plane algorithms in [19], at iteration \( K \geq 1 \), optimizing Eq. 7 is equivalent to optimizing the following equation:

\[
\min_{w} \max_{y \in \mathcal{Y}} \left\{ \frac{1}{2} \|w\|_2^2 + C \sum_{i,j} \max \left\{ 0, \hat{y}_{ij}^{(K)} w^T \phi(x_{ij}) + |\hat{y}_{ij}^{(K)}| \right\} \right\}
\]

s.t. \( \forall i, j, \hat{y}_{ij}^{(K)} \in \{-1, 0, 1\} \), \( \sum_j \hat{y}_{ij}^{(K)} = \sum_j y_{ij} \), \( \sum_i \hat{y}_{ij}^{(K)} = \sum_i y_{ij} \),

where \( \forall i, j, \hat{y}_{ij}^{(K)} = \sum_{k=1}^K (\hat{y}_{ij}^{(k)} - y_{ij}) \).

Accordingly, we show our learning algorithm for re-id in Alg. 1, where in each iteration we only need to update an auxiliary structure \( \hat{y} \) rather than updating the feature vectors in Eq. 7. In fact, updating \( \hat{y} \) is equivalent to updating the trade-off weight for each image pair in the bipartite graph, and then repeatedly learn a linear classifier with rescaled margin equal to 1. Notice that such procedure is widely used in hard negative mining [9, 16] to improve the classifier accuracy. In this way, we can efficiently solve a large-scale re-id problem with structured learning.

### 2.1.3 Testing

In order to compare the performances of difference methods, for each probe image, a ranking of matching individuals in the gallery set is produced, and the recognition rates using top \( r \) individuals are utilized for evaluation. In other words, the recognition rate is treated as a function of rank.

For our method, since we try to predict the matching structures, at each rank \( r \) we have to solve a matching problem with a fixed learned classifier. That is, we have to solve the following matching problem for rank \( r \):

\[
\max_{\bar{y} \in \mathcal{Y}} w^T f(x, \bar{y})
\]

s.t. \( \forall i, j, \bar{y}_{i,j} \in \{0, 1\} \), \( \sum_j \bar{y}_{ij} = r \), \( \sum_i \bar{y}_{ij} = r \).

Notice that here \( r \) denotes the number of individuals, not images. Thus if \( r = 1 \) we are looking for one individual to one individual matching during test-time. We can incorporate other scenarios such as multiple images associated with some individuals by appropriately modifying the constraints in Eq. 4.

### 2.2 Basis Functions for Person Re-Identification

We generally face two issues in visual recognition problems: (1) visual ambiguity [34] (i.e. the appearance of instances which belong to the same thing semantically can vary dramatically in different scenarios), (2) spatial displacement [9] of visual patterns.

While visual ambiguity can be somewhat handled through codebook construction and quantization of images into visual words, our goal of matching humans in re-id imposes additional challenges.
Humans body parts exhibit distinctive local visual patterns and these patterns systematically change appearance locally. Our goal is to account for this inherent variability in basis functions through co-occurrence matrices that quantify spatial and visual changes in appearance.

2.2.1 Locally Sensitive Co-occurrence Designs

We need co-occurrence models that not only account for the locality of appearance changes but also the random spatial & visual ambiguity inherent in vision problems. Therefore, we first construct a codebook \( Z = \{ z \} \subset \mathbb{R}^D \) with \( N \) codewords. Our codebook construction is global and thus only carries information about distinctive visual patterns. Nevertheless, for a sufficiently large codebook distinctive visual patterns are mapped to different elements of the codebook, which has the effect of preserving local visual patterns. Specifically, we map each pixel at 2D location \( \pi \in \Pi \) of image \( I \) into (at least one) codewords to cluster pixels.

To emphasize local appearance changes, we look at the spatial distribution of each codeword. Concretely, we let \( C(I, z) \subseteq \Pi \) denote the set of pixel locations associated with codeword \( z \) in image \( I \) and associate a spatial probability distribution, \( p(\pi | z, I) \), over this observed collection. In this way visual words are embedded into a family of spatial distributions. Intuitively it should now be clear that we can use the similarity (or distance) of two corresponding spatial distributions to quantify the pairwise relationship between two visual words. This makes sense because our visual words are spatially locally distributed and small distance between spatial distributions implies spatial locality. Together this leads to a model that accounts for local appearance changes.

While we can quantify the similarity between two distributions in a number of ways, the kernel mean embedding method is particularly convenient for our task. The basic idea to map the distribution, \( p \), into a reproducing kernel Hilbert space (RKHS), \( \mathcal{H} \), namely, \( p \rightarrow \mu_{p}(\cdot) = \sum K(\cdot, \pi)p(\pi) \triangleq E_{p}(K(\cdot, \pi)) \) for universal kernels, such as RBF kernels, this mapping is injective, i.e., the mapping preserves the information about the distribution \( \text{[32]} \). In addition we can exploit the reproducing property to express inner products in terms of expected values, namely, \( \langle \mu_{p}, \Phi \rangle = E_{p}(\Phi), \forall \Phi \in \mathcal{H} \) and obtain simple expressions for similarity between two distributions (and hence two visual words) because \( \mu_{p}(\cdot) \in \mathcal{H} \). To this end, consider the codeword \( z_m \) in image \( I^{(1)} \) and codeword \( z_n \) in image \( I^{(2)} \). The co-occurrence matrix (and hence the basis function) is the inner product of visual words in the RKHS space, namely,

\[
\phi(x_{ij})_{mn} = \langle \mu_{p_{1}}(z_m, I^{(1)}), \mu_{p_{2}}(z_n, I^{(2)}) \rangle = \sum_{\pi_u} \sum_{\pi_v} K(\pi_u, \pi_v)p(\pi_u | z_m, I^{(1)})p(\pi_v | z_n, I^{(2)}) \tag{5}
\]

where we have used the reproducing property in the last equality. We now have several choices for the kernel \( K(\pi_u, \pi_v) \) above. We list some of them here:

**Identity:** \( K(\cdot, \pi) = e_{\pi} \), where \( e_{\pi} \) is the usual unit vector at location \( \pi \). We get the basis function:

\[
\phi(x_{ij})_{mn} \propto |C(I^{(1)}|m, z_m) \cap C(I^{(2)}|n, z_n)|, \tag{6}
\]

where \( | \cdot | \) denotes set cardinality. This choice often leads to poor performance in re-id because it is not robust to spatial displacements of visual words, which we commonly encounter in re-id.

**Radial Basis Functions (RBF):** This leads to the following basis function:

\[
\phi(x_{ij})_{mn} = \sum_{\pi_u} \sum_{\pi_v} \exp \left( \frac{\| \pi_u - \pi_v \|^2}{2\sigma^2} \right)p(\pi_u | z_m, I^{(1)})p(\pi_v | z_n, I^{(2)}) \tag{7}
\]

The upper bound above is used for efficiently computing our basis function by removing the summation over \( \pi_v \). This basis function is often a better choice than the previous one because RBF accounts for some spatial displacements of visual words for appropriate choice of \( \sigma \).

**Latent Spatial Kernel:** This is a type of probability product kernel that has been previously proposed \( \text{[18]} \) to encode generative structures into discriminative learning methods. In our context we can view the presence of a codeword \( z_m \) at location \( \pi_u \) as a noisy displacement of a true latent location
The classifier is learned in the training stage using Alg. 1. The trade-off parameter $C$ can easily compute the operation using distance transform. By plugging this new $K$ into Eq. 5 we have

$$\phi(x_{ij}) = \sum_{u=1}^{n} \sum_{v=1}^{n} \sum_{h} \kappa_1(\pi_u, h) \kappa_2(\pi_v, h) p(h) p(\pi_u | z_m, I^{(1)}_i) p(\pi_v | z_n, I^{(2)}_j)$$

where the inequality follows by rearranging the summations and standard upper bounding techniques. Again we use an upper bound for computational efficiency. The main idea here is that by introducing the latent displacement variables, we have a handle on view-specific distortions observed in the two cameras. As we will see later, these latent kernels result in superior performance.

### 3 Implementation

We illustrate the schematics of our method during testing in Fig. 3. For each image, a 672-dim ColorSIFT feature vector is extracted for a $10 \times 10$ pixel patch centered at every possible pixel. Further, we decorrelate each feature using the statistics learned from training data, as suggested in [15].

For codebook construction, we randomly sample 1000 patch features per image in the training set, and cluster these features into a codebook using K-Means. Then we encode each patch feature in images from the probe and gallery sets into a codeword whose Euclidean distance to the patch feature is the minimum among all the codewords. As a result, each image is mapped into a codeword image whose pixels are represented by the indices of the corresponding encoded codewords.

In this way, the spatial probability $p(\pi | z, I)$ is approximated by $p(\pi | z, I) = \frac{\sum_{I'} I'(\pi, z, I')}\. The classifier is learned in the training stage using Alg. [1]. The trade-off parameter $C$ in Eq. [1] is set using cross-validation. During testing, we follow Section 2.1.3 to perform re-identification.

### 4 Experiments & Discussions

We test our method on two benchmark datasets, VIPeR [12] and CUHK Campus [38]. Images from the probe set are treated as queries and compared with every person in the gallery set. For each query, our method produces a ranking of matching individuals in the gallery set. Performance can

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[1] The authors’ code can be downloaded at [http://www.ee.cuhk.edu.hk/~rzhao/](http://www.ee.cuhk.edu.hk/~rzhao/)
be evaluated with these resultant rankings, since the identity label of each image is known. The rankings for every query is combined into a Cumulative Match Characteristic (CMC) curve, which is a standard metric for re-identification performance. The CMC curve displays an algorithm’s recognition rate as a function of rank. For instance, a recognition rate at rank-\(r\) on the CMC curve denotes what proportion of queries were correctly matched to a corresponding gallery individual at rank-\(r\) or better. Experimental results are reported as the average CMC curve over 3 trials.

4.1 Datasets

VIPeR \cite{13} is comprised of 632 different pedestrians captured in two different camera views, denoted by CAM-A and CAM-B, respectively. Each image is normalized to 128×48 pixels. We followed the experimental set up described in \cite{38}. The dataset is split in half randomly, one partition for training and the other for testing. Samples from CAM-A form the probe set, and samples from CAM-B form the gallery set. The parameter \(\sigma\) in the RBF kernels is set to 3 for this dataset.

CUHK Campus \cite{38,22} consists of 1816 people captured from five different camera pairs, labeled P1 to P5. Each image contains 160×60 pixels. Following the experimental settings from \cite{38} and \cite{22}, we use only images captured from P1, consisting of 971 people in two camera views denoted CAM-1 and CAM-2, respectively. Each camera view has 2 images for each person. We randomly select 485 individuals from the dataset for training, and the rest of the, 486, are used for testing. The gallery and probe sets are formed by CAM-1 and CAM-2, respectively, and note that during testing we know the labels for gallery images. To re-identify a person, we compare every probe image with every gallery image, leading to 486×2=972 decision scores. Then per person in the gallery set, we average the 2 decision scores belonging to this person as the final score for ranking later. Here the parameter \(\sigma\) in the RBF kernels is set to 6, since the image size is larger.

4.2 Comparisons with Different Structures and Basis Functions

We implement three algorithms. The first is \(S_0\) which is a linear SVM but trained with latent basis function Eq. 8. For baseline comparison we test \(S_0\) in the conventional way, i.e., each probe is taken in isolation and scored against gallery images. Highest scoring ones are returned as matches. Our second algorithm uses structured learning with structure \(S_1\) as shown in Fig. 2(a). The third algorithm, \(S_2\), uses the structure of Fig. 2(b) during training and with testing similar to \(S_1\). This is closer to linear SVMs in spirit but trained with the structure prediction setting of Eq. 1. During testing we use bipartite matching by simultaneously matching all images in the probe.

We experiment with several basis functions for \(S_1\) to understand its importance. (i) Identity basis function using Eq. 6. This feature does not incorporate spatial displacements. (ii) RBF basis function using Eq. 7. (iii) Latent spatial basis function using Eq. 8. (iv) Spatial Pyramid Bag-of-Words (SP) basis function. We implement the spatial pyramid representation in \cite{21} as features. The pyramid is constructed up to Level 4, leading to \(1 + 4 + 9 + 16 + 64 = 94\) spatial cells, which matches the codebook size of 100 in our experiments and ensures fairness in our comparisons. For the basis functions we use the standard histogram intersection operation. Note that this method reflects shared visual patterns in the two views and does not account for changes in patterns. (v) Spatial Co-occurrence (SC) basis function. We take the codeword pairs at the same pixel locations as new “visual patterns”, and utilize their frequencies as our basis function.

4.3 Performance Comparisons

We compare different basis functions in Fig. 3 by holding the learning and testing structure fixed (algorithm \(S_1\) with 100 codewords). We observe that: (1) Identity basis functions consistently performs poorly thus pointing to the importance of spatial sensitivity. (2) SP basis functions consistently performs worse than the other three basis functions that account for spatial and co-occurrence information. This shows the importance of incorporating codeword co-occurrence. (3) As we expected the latent spatial basis function consistently outperforms all the other kernels.

To understand whether or not our method accounts for semantically meaningful appearance changes we look at which co-occurrence patterns are positively and negatively weighted using structure \(S_1\).

\footnote{We thank the authors for the response to their experimental settings.}
Figure 4: Matching rate comparison with different basis functions using 100 codewords on the two datasets.

Figure 6: Matching rate comparison between different methods on (a) VIPeR and (b) CUHK Campus datasets. Expect for our results, the other CMC curves are cited from [38]. This figure is best viewed in color.

As shown in Fig. 5, people in images for re-id have roughly consistent structures, e.g. head on top and legs at the bottom. Local sensitivity assigns higher weights to codeword co-occurrences with small spatial distances and preventing distant codewords from being matched (e.g. head-legs). Evidently, co-occurrence patterns “transfer” information from different views into a common space as shown in Fig. 5. Under different lighting conditions color “white” may turn into “light blue”, but not into “dark blue”. Latent spatial kernels implicitly incorporates likelihood of noisy displacements of co-occurring visual words, e.g. head locating at top-left, top-middle, or top-right (with slight spatial displacement from its default location). In summary latent spatial basis function is discriminative and provides robust pair-wise image descriptors for re-id tasks.

Fig. 6 shows our matching rate comparison with other methods on the two datasets. Here we report the best performances for both of our methods using different ground-truth matching structures $S_1$ and $S_2$ by roughly tuning the number of codewords from 100 to 500, step by 100. For baseline comparison we also plot the algorithm $S_0$. We notice clearly that while latent basis kernel (with no structure) by itself contributes to performance improvement, incorporating structure results in even better performance. At rank-1, our method achieves the matching rates of 38.92% and 56.69%, respectively, beating the state-of-the-art results in [38] by 8.76% and 28.24%.

Several questions arise that is subject of future work. It would be useful to reduce the computational complexity of calculating our pair-wise latent spatial basis functions. One possibility is to modify the structured learning algorithm by decomposing the parameter $w$ into two separable parameters, because our basis function can be decomposed into two parts, one from the probe image and the other from the gallery image. Such a decomposition will accelerate the computation. Second, it is worth understanding why we obtain different levels of performance for different learning structures ($S_1$ vs. $S_2$) and which structure would be optimal for re-id.
