Video-based Person Re-identification Using Spatial-Temporal Attention Networks

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ABSTRACT

We consider the problem of video-based person re-identification. The goal is to identify a person from videos captured under different cameras. In this paper, we propose an efficient spatial-temporal attention based model for person re-identification from videos. Our method generates an attention score for each frame based on frame-level features. The attention scores of all frames in a video are used to produce a weighted feature vector for the input video. Unlike most existing deep learning methods that use global representation, our approach focuses on attention scores. Extensive experiments on two benchmark datasets demonstrate that our method achieves the state-of-the-art performance. Code is available at https://github.com/shivansh/Spatial-Temporal-attention.

CCS CONCEPTS

• Computing methodologies → Computer vision; Object identification;

KEYWORDS

Person Re-Identification, Attention Mechanism

1 INTRODUCTION

In this paper, our goal is to solve the problem of video-based person re-identification. Given a video containing a person, the goal is to identify the same person from other videos possibly captured under different cameras. Person re-identification is useful in a wide range of applications, e.g. video surveillance, police investigation, etc. A common strategy for person re-identification is to formulate it as a metric learning problem. Given the query video and a candidate video, the goal is to develop algorithms to compute the distance between these two videos. If the distance is small, it means the two videos likely contain the same person. See Figure 1 for an illustration. Previous work in person re-identification falls into two broad categories: image-based re-identification and video-based re-identification. Earlier work [10, 17, 19, 20, 22, 26, 28, 31] in this area focuses on the former, where the inputs to these systems are pairs of images and the goal is to identify whether they are images of the same person. Recently, video-based person re-identification is receiving increasing attention [8, 12, 16, 21, 24, 32, 33]. Compared with static images, video-based person re-identification is a more natural setting for practical applications such as video surveillance.

Person re-identification (either image or video based) is a challenging problem since the images/videos are often captured under different camera views. This can cause large variations in illumination, body pose, viewpoint, etc. Compared with static images, the temporal information in videos can potentially provide additional information that can help disambiguate the identity of a person. Previous work in this area has explored ways of exploiting this temporal information. A common strategy [16, 24, 32] is to use temporal pooling to combine frame-level features to represent the entire video sequence. Then this video-level feature vector can be used for re-identification.

Previous work [24, 32] has made the observation that not all frames in a video are informative. For example, if the person is occluded in a frame, ideally we would like the feature representation of the video to ignore this frame and focus on other useful frames. A natural way of solving this problem is to use the attention models [1, 18, 23] that have been popular in visual recognition recently. In [24, 32], RNN is used to model the temporal information of the frames and generate the attention score for each frame for person re-identification.

In this paper, we propose a new attention model for video-based re-identification. Compared with previous works [24, 32], our model has several novelties. First, instead of using RNN, we directly produce the attention score of each frame based on the image feature of this frame. Our experimental results show that this simpler method outperforms RNN-based attention method. Since the attention score of each frame is calculated based on the frame, the computation of attention scores over all frames can be easily made parallel and take full advantage of the GPU hardware. Second we propose a new spatio-temporal attention model that allows useful information to be extracted from each frame without succumbing to occlusions and misalignments.

Our contributions include:

1. A new attention mechanism for video-based person re-identification. Unlike previous work [32] that uses RNN to generate the attentions, our model directly generates attentions based on frame-based features. As a consequence, the computation of the attentions is much simpler and can be easily parallelized. In contrast, RNN has to process frames in a sequential order, so the computation cannot be made parallel. Despite of its simplicity, our model outperforms the more sophisticated RNN-based attention mechanism in [32].

2. Our newly designed network learns multiple spatial attention along with temporal attention. In order to represent the overall spatial attention of the frame, we need multiple hops of attention [11] that focus on different parts of the frame. In addition, we also study
the effect of incrementing the value of number of hops of spatial attention.

2 RELATED WORK
There has been extensive work on person re-identification from static images. Early work in this area uses hand-crafted feature representations [3, 9, 14, 15, 30]. Most of these methods involve extracting feature representations that are invariant to viewpoint changes, then learning a distance metric to measure the similarity of two images.

Deep learning approaches, in particular deep convolutional neural networks (CNNs), have achieved tremendous successes in various visual recognition tasks [7]. In many areas of computer vision, CNNs have replaced hand-engineering feature representations with features learned end-to-end from data. Recently, CNNs have been used for image-based person re-identification [10, 17, 19, 20, 22, 26, 28, 31]. These methods use deep network architecture such as Siamese network [4] to map images to feature vectors. These feature vectors can then be used for re-identification. Although the performance of image-based person re-identification has increased significantly, this is not a very realistic setting for practical applications. To address the limitation of image-based re-identification, a lot of recent work has begun to explore video-based re-identification [8, 12, 16, 21, 24, 25, 32, 33] since it is closer to real-world application settings. Compared with static images, videos contain temporal information that is potentially distinctive for differentiating a person’s identity. Some prior work has explored ways of incorporating temporal information in deep convolutional neural network for re-identification. For example, McLaughlin et al. [16] use CNN on each frame in a video and incorporate a recurrent layer on the CNN features. Temporal pooling is then used to combine frame-level features into a single video-level feature vector for re-identification.

Our work is also related to a line of research on incorporating attention mechanism in deep neural networks. The attention mechanism allows the neural networks to focus on part of the input and ignore the irrelevant information. It has been successfully used in many applications, including machine translation [1], image captioning [23], visual question answering [18], etc. In video-based re-identification, the attention mechanism has also been explored [24, 32]. The intuition is that only a small portion of the video contains informative information for re-identification. So the attention mechanism can be used to help the model focus on the informative part of the video.

The work in [32] is the closest to ours. It uses an RNN to generate temporal attentions over frames, so that the model can focus on the most discriminative frames in a video for re-identification. In this paper, we use temporal attentions over frames as well. But instead of using RNN-based models to generate attentions [32], we directly calculate the attention scores based on frame-based features. This makes the model much simpler and the computation of attention scores can be easily parallelized over frames. We also propose propose a new spatio-temporal attention model wherein we calculate multiple spatial attention over the frames. We demonstrate that this multiple spatial attention mechanism improves the performance of the final model.
3 OUR APPROACH

Figure 2 shows the overall architecture of our proposed approach based on the Siamese network [4]. The input to the Siamese network is a pair of video sequences corresponding to the query video and the candidate video to be compared. The output of the Siamese network is a scalar value indicating how likely these two videos contain the same person. Each video goes into one of the two branches of the Siamese network. Each branch of the Siamese network is a Convolutional neural network used to extract the features of the input video. The parameters of two branches of the Siamese network are shared. Finally, the features from the two input videos are compared to produce the final output.

When a video goes through one of the two branches of the Siamese network, we first extract per-frame features on each frame of the input video. Then we compute an attention score on each frame indicating how important this frame is for the re-identification task. The intuition is that not all frames in a video are informative. The attention scores enable our model to ignore certain frames and only pay attention to informative frames in the video. The attention scores are then used to aggregate per-frame visual features weighted by the corresponding attention score to form a feature vector for the entire video sequence. Along with calculation of temporal attention we also calculate the spatial attention for multiple hops over the input frame. Here the intuition is that in order to pay attention to multiple parts of the frame we need multiple attentions over it, which now allows useful information to be extracted without being hindered by occlusions and misalignments. We can repeat this process for several hops of attention (see Sec. 4.4), where each hop produces attention scores that focus more on the informative frames. Finally, the features of two input videos are compared to produce the output.

3.1 Frame-Level Features

Similar to [16], we extract frame-level features using both RGB color and optical flow channels. The colors contain information about the appearance of a person, while the optical flows contain information about the movement of the person. Intuitively, both of them are useful to differentiate the identity of the person. As a preprocessing step, we convert all the input images (i.e. video frames) from RGB to YUV color space. We normalize each color channel to have a zero mean and unit variance. The Lucas-Kanade algorithm [13] is used to calculate both vertical and horizontal optical flow channels on each frame. We resize each frame to have a spatial dimension of 56 × 40. The optical flow field F of the frame is split into two scalar fields Fx and Fy corresponding to the x and y components of the optical flow. In the end, each frame is represented as a 56 × 40 × 5 input, where the 5 channels correspond to 3 color channels (RGB) and 2 optical flow channels (x and y). We fine-tuned CNN architecture of [16] to extract frame-level features for an input video. The CNN architecture (shown in Fig. 3) consists of three stages of convolution, max-pooling, and nonlinear (tanh) activations. Each convolution filter uses 5 × 5 kernels with 1 × 1 stride and 4 × 4 zero padding. A fully connected layer is used in the end to produce a 128-dimensional feature vector. Given T frames in an input video, the CNN model is applied on each input frame of the video. In the end, CNN produces a 128-dimensional feature vector (i.e. \( x_i \in \mathbb{R}^{128} \)) to represent each frame \( x_i \) (i= 1,2,...,T) in the input video.

3.2 Temporal Attention Network

Motivated by the recent success of attention based models [1, 2, 23, 27], we propose an attention based approach for re-identifying person from videos. The intuition behind the attention based approach is inspired by the human visual processing [24]. Human brains often pay attention to different regions of different sequences when trying to re-identify persons from videos. Based on this intuition, we propose a deep Siamese architecture where each branch generates attention scores of different frames based on the frame-level CNN features. The attention score of a frame indicates the importance of this frame for the re-identification task.

As shown in Figure 2, each input video sequence (sequence of frames with optical flow) is passed to the CNN to extract frame-level
3.3 Spatial Attention Network

For the task of person re-identification, due to several real time issues such as the overlooking angle of most of the surveillance equipments, the pedestrians who are captured only take a part in whole spatial images. Therefore, local spatial attention is necessary for deep networks such that useful information is extracted from each frame without getting hindered by problems such as occlusions and misalignments, and thus in this way superfluous information can be removed. In addition we employ multiple spatial attention model which can help us pay attention to multiple parts of the frame by hopping multiple times over it. In the experiment section, we will show that this multiple attention mechanism improves the performance of our model.

The basic idea of our spatial attention network is to pass the frame level features as input to the spatial attention network which has a convolution layer followed by sigmoid. Note that since our method evalulates multiple attention (see Fig.4), we will get j (where j is number of attention layers) feature vectors from the spatial attention network. The convolution filter, conv_j(·), uses 5 × 5 kernels with 1 × 1 stride and 2 × 2 padding. α^j_i is the attention matrix which is multiplied by the frame level features x_i to get the weighted attention features as follows:

\[
α^j_i = σ(\text{conv}_j(x_i)), \quad i = 1, \cdots, T
\]

\[
f^j_i = \sum_{i=1}^{T} α^j_i x_i, \quad i = 1, \cdots, T
\]

where \(f^j_i\) is the spatial attention feature vector of the input video. Now we add spatial attention feature vector \(f^j\) and temporal attention feature vector \(f^t\) and then sum it up for all attention layers to get the final feature vector as follows:

\[
F_j = f^j + f^t
\]

\[
F = \sum_j F_j
\]

We find out empirically the value of j to be 3 (See section 4.4 for more details).

3.4 Model Learning

Our model is a form of the Siamese network (Figure 2). It has two identical branches with shared parameters. The detail architecture of each branch is shown in Figure 4. Let \(F_1\) and \(F_2\) be the feature vectors of two input videos from the Siamese network. We now calculate Euclidean distance between the feature vectors in a manner similar to [16, 24] and apply the squared hinge loss (Loss\_hinge) as follows:

\[
L_{\text{hinge}} = \frac{1}{2} \|F_1 - F_2\|^2, \quad \frac{1}{2} \max(0, m - \|F_1 - F_2\|), \quad X_1 = X_2
\]

\[
X_1 \neq X_2
\]

where the hyper-parameter m represents the margin of separating two classes in \(L_{\text{hinge}}\). Here we use \(X_1\) and \(X_2\) to represent the identities of the persons from two input videos. The idea is that if the two videos contain the same person (i.e. \(X_1 = X_2\)) the distance between the feature vectors should be small. Otherwise, the distance should be large if the persons are different (i.e. \(X_1 \neq X_2\)). Similar to [16], we also use another loss (i.e. identity loss Loss\_id) to each

\[
L_{\text{id}} = \frac{1}{2} \max(0, m - \|F_1 - F_2\|), \quad X_1 = X_2
\]

\[
X_1 \neq X_2
\]
Figure 4: Illustration of our proposed attention network architecture. Attention module consists of 2 branches, in the temporal branch (upper) we generate N attention scores by applying linear mapping on the feature vectors followed by a sigmoid function. In the lower branch we calculate multiple spatial attention over the frame level features followed by a sigmoid function, spatial attention features are then added with temporal attention features to form final attention scores for the entire video.

branch of the Siamese network to predict the person’s identity. We use a linear classifier to predict one of the person’s identity from the feature vector extracted through each branch of the Siamese network. We then apply a Softmax loss over the prediction for each Siamese branch. The final loss is the combination of two identity losses (\(L_{id1}\) and \(L_{id2}\)) from each Siamese branch and the hinge loss as follows:

\[
L_{final} = L_{id1} + L_{hinge} + L_{id2}
\]  

We use stochastic gradient decent to optimize the loss function define in Eq. 8. After training, we only use the feature vectors to compute the distance between two input videos for re-identification.

4 EXPERIMENTS

In this section, we firstly introduce the datasets used in our experiments (Sec. 4.1). We then describe the experimental setup and some implementation details (Sec. 4.2). We present the results of experiment in Sec 4.3 and Sec 4.4.

4.1 Datasets

We conduct experiments on two benchmark datasets: iLIDS-VID [21] and PRID-2011 [6].

iLIDS-VID Dataset: This dataset consists of video sequences of 300 persons where each person is captured by a pair of non-overlapping cameras. The length of each video sequence varies from 23 to 192 frames with an average of 73 frames. The dataset is quite challenging due to lot of occlusions, illumination changes, background clutters and so on.

PRID-2011 Dataset: This dataset contains video sequences of 749 persons. For the first 200 persons (or identities), there are two video sequences captured by two different cameras. The remaining persons appear in only one camera. Each sequence contains between 5 to 675 frames, with an average of 100 frames. In terms of complexity this dataset is relatively simple than iLIDS-VID.

Some sample frames of these three datasets are shown in Figure 5. Table 1 shows the summary of these two benchmark datasets.
Figure 5: Sample images of two benchmark datasets used in our experiments. The first two rows show sample images from the iLIDS-VID dataset captured by two different cameras. The next two rows show sample images from the PRID-2011 dataset.

Table 1: Summary of basic information of the two datasets used in our experiments.

| Dataset          | iLIDS-VID | PRID-2011 |
|------------------|-----------|-----------|
| Total no. of id. | 300       | 749       |
| No. id in multiple cameras | 300  | 200     |
| No. track-lets  | 600       | 400       |
| No. of boxes    | 44k       | 40k       |
| Image resolution| 64x128    | 64x128    |
| No. of camera   | 2         | 2         |
| Detection procedure | hand     | hand     |
| Complexity      | Challenging | Simple    |

4.2 Setup and Implementation Details

We follow the experiment protocol of McLaughlin et al. [16]. On each of the two datasets (iLIDS-VID and PRID-2011), we randomly split the dataset into two equal subsets where one subset is used for training and remaining one for testing. For evaluating our proposed method, we use the Cumulative Matching Characteristics (CMC) curve which is a ranking based evaluation metric. In the ideal case, the ground-truth video sequence should have the highest rank. For each dataset, we repeat the experiment 10 times and report the average result over these 10 runs. In each run, we randomly split the dataset into training/test sets. Standard data augmentation techniques, such as cropping and mirroring, are applied to increase the amount of training data. We initialize the weights in the network using the initialization technique in [5]. For training our network, we consider equal numbers of positive and negative samples. We set the margin in the hinge loss (Eq. 7) as \( m = 2 \). The network is trained for 1100 epochs with a batch size of one. The learning rate in the stochastic gradient descent is set to be \( 10^{-4} \). Due to the variable-length of video sequences in both datasets, we use sub-sequences of 16 consecutive frames (\( T = 16 \)) during training. Sometimes, this length is greater than the real sequence length. In that case, we consider the whole set of images (frames) as the sub-sequence. A full epoch consists of a pair of positive and negative sample. During testing, we consider a video sequence captured by the first camera as the probe sequence and a video sequence captured by the second camera as a gallery sequence. We use at most 128 frames in a testing video sequence. Again, if the length is greater than the real sequence, we consider the whole set of images as the video sequence. Similar strategies have been used in previous work [16].

4.3 Results

We present the results on the two benchmark datasets and compare with other state-of-the-art methods in Table 2 and Table 3. From...
the CMC rank, we see that our method outperforms all other state-of-the-art methods by nearly 4% and 11% on rank-1 accuracy on the iLIDS-VID and PRID-2011 dataset respectively. Figure 6 shows some qualitative retrieval results after applying our proposed method on the challenging iLIDS-VID dataset. We also show some failure cases in Figure 7.

Table 2: Comparison of our proposed approach with other state-of-the-art methods on the iLIDS-VID dataset in terms of CMC(%) at different ranks.

| Dataset     | iLIDS-VID | Method              | Rank-1 | Rank-5 | Rank-10 | Rank-20 |
|-------------|-----------|---------------------|--------|--------|---------|---------|
| Ours        |           | Xu et al.[26]       | 62     | 86     | 94      | 98      |
|             |           | Zhou et al.[35]     | 55.2   | 86.5   | -       | 97      |
|             |           | McLaughlin et al.[18] | 58    | 84     | 91      | 96      |
|             |           | Yan et al.[27]      | 49.3   | 76.8   | 85.3    | 90.1    |
|             |           | STA[14]             | 44.3   | 71.7   | 83.7    | 91.7    |
|             |           | VR[23]              | 35     | 57     | 68      | 78      |
|             |           | SRID[8]             | 25     | 45     | 56      | 66      |
|             |           | AFDA[10]            | 38     | 63     | 73      | 82      |
|             |           | DTL [7]             | 26     | 48     | 57      | 69      |

Table 3: Comparison of our proposed approach with other state-of-the-art methods on the PRID-2011 dataset in terms of CMC(%) at different ranks.

| Dataset     | PRID-2011 | Method              | Rank-1 | Rank-5 | Rank-10 | Rank-20 |
|-------------|-----------|---------------------|--------|--------|---------|---------|
| Ours        |           | Xu et al.[26]       | 77     | 95     | 99      | 99      |
|             |           | Zhou et al.[35]     | 79.4   | 94.4   | -       | 99.3    |
|             |           | McLaughlin et al.[18] | 70    | 90     | 95      | 97      |
|             |           | Yan et al.[27]      | 58.2   | 85.8   | 93.7    | 98.4    |
|             |           | STA[14]             | 64.1   | 87.3   | 89.9    | 92      |
|             |           | VR[23]              | 42     | 65     | 78      | 89      |
|             |           | SRID[8]             | 35     | 59     | 70      | 80      |
|             |           | AFDA[10]            | 43     | 73     | 85      | 92      |
|             |           | DTL [7]             | 41     | 70     | 78      | 86      |

4.4 Effect of Multiple Attention

We conduct empirical study on the training set of the iLIDS-VID and PRID-2011 dataset to analyze the effect of the multiple attention on the overall performance of the proposed network. We train the model on the training videos and report the performance (CMC%) on the validation set for different number of attention layers in Table 4 and Table 5 respectively.

We observe that the performance gradually improves until number of attention layer is 3. After that, the performance starts to drop. Based on this empirical result, we choose number of attention layers as 3 in our experiments. It can also be observed from Table 4 and Table 5 that when the number of attention layers is 0, i.e. when we do not incorporate the concept of spatial attention the accuracies fall by a huge margin.

Table 4: Performance for different number of attention layers on the iLIDS-VID dataset. Again, we report the performance in terms of CMC %

| Dataset     | iLIDS-VID | No. of Att. layers | Rank-1 | Rank-5 | Rank-10 | Rank-20 |
|-------------|-----------|--------------------|--------|--------|---------|---------|
| Ours        |           | 3                  | 66     | 90     | 95      | 99      |
|             |           | 2                  | 64     | 88     | 95      | 99      |
|             |           | 1                  | 63     | 88     | 95      | 98      |
|             |           | 0                  | 60     | 88     | 94      | 98      |

Table 5: Performance for different number of attention layers on the PRID-2011 dataset. Again, we report the performance in terms of CMC %

| Dataset     | PRID-2011 | No. of Att. layers | Rank-1 | Rank-5 | Rank-10 | Rank-20 |
|-------------|-----------|--------------------|--------|--------|---------|---------|
| Ours        |           | 3                  | 88     | 97     | 99      | 99      |
|             |           | 2                  | 84     | 96     | 99      | 99      |
|             |           | 1                  | 80     | 95     | 98      | 99      |
|             |           | 0                  | 80     | 96     | 99      | 99      |

5 CONCLUSIONS

In this paper, we have proposed an attention-based deep architecture for video-based re-identification. The attention module calculates frame-level attention scores, where the attention score indicates the importance of a particular frame. We perform experiments on two benchmark datasets and compare with other state-of-the-art approaches. We demonstrate that our proposed method outperforms other state-of-the-art approaches.

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Figure 6: Qualitative retrieval results of our proposed method on the challenging iLIDS-VID dataset. The first column represents the probe video sequence. The remaining columns correspond to retrieved video sequences sorted by their distances to the probe video sequence. Here, we use a single image to represent each retrieved video sequence. The green boxes indicate the ground-truth matches. We can see that the ground-truth matches are ranked very high in the list.

Figure 7: Examples of some failure case of our proposed method. The first row indicates the probe sequence where single image in second row represents retrieve gallery sequence of corresponding person.
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