AAformer: Auto-Aligned Transformer for Person Re-Identification

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Abstract—In person re-identification (re-ID), extracting part-level features from person images has been verified to be crucial to offer fine-grained information. Most of the existing CNN-based methods only locate the human parts coarsely, or rely on pretrained human parsing models and fail in locating the identifiable nonhuman parts (e.g., knapsack). In this article, we introduce an alignment scheme in transformer architecture for the first time and propose the auto-aligned transformer (AAformer) to automatically locate both the human parts and nonhuman ones at patch level. We introduce the “Part tokens ([PART]s),” which are learnable vectors, to extract part features in the transformer. A [PART] only interacts with a local subset of patches in self-attention and learns to be the part representation. To adaptively group the image patches into different subsets, we design the auto-alignment. Auto-alignment employs a fast variant of optimal transport (OT) algorithm to online cluster the patch embeddings into several groups with the [PART]s as their prototypes. AAformer integrates the part alignment into the self-attention and the output [PART]s can be directly used as part features for retrieval. Extensive experiments validate the effectiveness of [PART]s and the superiority of AAformer over various state-of-the-art methods.

Index Terms—Auto-alignment, part-level representation, person re-identification (re-ID), transformer.

I. INTRODUCTION

PERSON re-identification (re-ID) aims to associate the specific person across cameras. Lots of existing convolutional network-based methods extract part-level features to obtain fine-grained information to alleviate the body part misalignment problem, which can be caused by inaccurate person detection, human pose variations, and the changing of camera viewpoints. The stripe-based methods [1], [3] design stripe-based image partitions to locate human parts. Some methods adopt pretrained human parsing models [2] to locate human parts of fine granularity. These methods either cannot well align the human parts or fail in locating the identifiable nonhuman parts like knapsack [4].

Recently, the self-attention-based architecture, transformer [5], has shown its scalability and effectiveness in many computer vision tasks. ViT [6] first employs transformer architecture to conduct image recognition. They divide the input image into fixed-size patches, linearly embed each of them, and feed them to a transformer encoder to obtain the image representation. TransReID [7] proposes to apply the ViT to object re-ID. They design patch shuffle operations and introduce side information like camera/view IDs to learn robust features, validating the superiority of transformer in re-ID tasks. As they do not take the misalignment issue into consideration, the part alignment scheme in the transformer architecture is still unexplored.

In this article, we propose a specific alignment scheme for the transformer and also alleviate the problems of existing methods, i.e., aligning human parts coarsely and failing in locating nonhuman parts. The proposed auto-aligned transformer (AAformer) integrates the part alignment into the self-attention and adaptively locates both the human parts and nonhuman ones at patch level in an online manner.

First, we propose the “Part tokens ([PART]s),” which are learnable vectors, for the transformer to learn the representations of local parts. Several [PART]s are concatenated to the sequence of patch embeddings and subsequently fed to the transformer encoder. In self-attention, a [PART] only attends to a local subset of patch embeddings and learns to represent the subset, which is shown in the first row of Fig. 1. The existing CNN-based methods can be transferred to the transformer by...
We employ a fast variant of OT algorithm [8] to online cluster adaptively group the image patches into different subsets. In the second row of Fig. 1, showing the problems of aligning [PART]s, e.g., PCB [1] and SPReID [2], which are illustrated one, are adaptively grouped to the identical [PART]. The image patches of the same part, which can be a human part or nonhuman partitioning [2]. (d) Toy example of the proposed auto-alignment mechanism. The image patches of the same semantic part are gathered to several groups with the [PART]s as subset. (b) [PART]s with PCB’s partitioning [1]. (c) [PART]s with SPReID’s partitioning [2].

Fig. 1. (a) Illustration of the added [PART]s. A [PART] only interacts with a subset of the patch embeddings and thus can learn to represent the subset. (b) [PART]s with PCB’s partitioning [1]. (c) [PART]s with SPReID’s partitioning [2]. (d) Toy example of the proposed auto-alignment mechanism. The image patches of the same part, which can be a human part or nonhuman one, are adaptively grouped to the identical [PART].

[PART]s, e.g., PCB [1] and SPReID [2], which are illustrated in the second row of Fig. 1, showing the problems of aligning human parts coarsely and failing in locating nonhuman parts. By means of the [PART], we propose the AAFormer to adaptively group the image patches into different subsets. We employ a fast variant of OT algorithm [8] to online cluster the patch embeddings into several groups with the [PART]s as their prototypes (e.g., leg prototype, knapsack prototype). The patch embeddings of the same semantic part are gathered to the identical [PART] and the [PART] only interacts with these patch embeddings. Given an input image, the output [PART]s of AAFormer learn to be different part prototypes of patch subsets of the input image and can be directly used as part features for re-ID. A toy example of this auto-alignment is shown in the last row of Fig. 1. In each layer of AAFormer, we sequentially conduct the auto-alignment to align the body parts and the self-attention to learn the part representations in the feedforward propagation. Therefore, AAFormer is an online method that simultaneously learns both part alignment and part representations, locating both human parts and nonhuman ones more accurately.

The contributions of this work are summarized as follows.

1) We introduce the “Part tokens ([PART]s)” for the transformer to learn part features and integrate the part alignment into the self-attention. A [PART] only interacts with a subset of patch embeddings, and thus can learn to be the local representation.

2) We further propose the AAFormer to adaptively locate the human parts and nonhuman ones online. Instead of using a predefined fixed patch assignment, AAFormer simultaneously learns both part alignment and part representations.

3) Extensive experiments validate the effectiveness of [PART] and the superiority of AAFormer over various state-of-the-art methods on the widely used benchmarks, i.e., Market-1501 [9], CUHK03 [10], DukeMTMC-reID [11], and MSMT17 [12].

The rest of this article is arranged as follows. Section II reviews some works related to this article. Section III introduces the main architecture of the proposed method and expounds the proposed method in detail. Section IV shows the good performance of the proposed method, compares it with the state-of-the-art methods, and analyzes the reasons why the proposed method is effective. Section V summarizes the full article.

II. RELATED WORK

A. Aligned Person Re-ID

Lots of existing CNN-based person re-ID approaches focus on global representation learning of identity-discriminative information, e.g., IDE network learning [10], [13], [14], [15], [16], [17] and metric learning [18], [19], [20], [21], [22], [23]. However, the lacking of explicit alignment mechanism largely limits their performance. To remedy this, many efforts have been made to develop the aligned person re-ID, which aims to extract part-level features. These methods could be roughly summarized into the following streams.

1) Stripe-Based Approaches: Some researchers develop stripe-based methods to extract part features. They directly partition the person images into several fixed horizontal stripes. PCB [1] first equally partitions the person images and then adopts part classifiers to refine each part in an attention-like manner. MGN [3] enhances the robustness by dividing images into stripes of different granularities and designs that overlap between stripes. However, these stripes are too coarse and with fixed heights and positions but do not correspond to specific semantic parts, and therefore fail in aligning different human parts well. Besides, there still remains much background noise in their stripes. Compared with these methods, our AAFormer can adaptively locate different local parts at patch level, which is more accurate.

2) Bounding Box-Based Approaches: Some works propose to locate the local parts by incorporating a bounding box selection subnetwork [24], [25], [26]. MSCAN [24] employs the spatial transformer networks (STN) [27] to locate the latent discriminative parts and subsequently extracts the part-level features. Deep representation learning with part loss (DPL) [25] proposes to generate bounding boxes from saliency maps and then extract part-level features from these parts. However, the shape of the located areas of these methods is limited to the rectangle, thus the located human parts are still coarse. Besides, there is usually much overlap between the bounding boxes predicted by these methods. In contrast, AAFormer can adaptively locate different discriminative parts with arbitrary shapes and ensure that there is no overlap between each part.

3) Extra Semantics-Based Methods: Some other works employ extra semantics to locate human parts.
SPReID [2] proposes to employ a pretrained human semantic parsing model to provide the mask of body parts for alignment. Part segmentation (PS) [28] adapts the human segmentation model to conduct the part awareness learning process. Convolutional deformable part models (CDPM) [29] also proposes to use the human parsing results to align the human body part in the vertical direction. DSA-reID [30] adopts dense extra semantic information of 24 regions for a person. However, the identifiable personal belongings like knapsack and reticule, which are crucial for person re-ID, cannot be recognized by the pretrained models and are ignored as background. Besides, the accuracy of extra semantics heavily counts on the pretrained human parsing models or the pose estimators. And these approaches cannot re-correct the errors of semantic estimation in their training processes. In contrast, AAformer can adaptively locate all the identifiable parts including both the human parts and nonhuman ones, and the adaptive patch assignment is conducted online in every layer of AAformer, so even if some patches are assigned incorrectly in one AAformer layer, other layers can also make the right patch assignment, which increases the robustness.

4) **Attention-Based Methods:** Attention mechanism constructs alignment by suppressing background noise and enhancing the discriminative regions [31], [32], [33], [34], [35], [36]. HA-CNN [32] formulates the harmonious attention CNN model by joint learning of soft pixel attention and hard regional attention. MHN [31] utilizes the complex and high-order statistics information in the attention mechanism, so as to capture the subtle but discriminative foreground areas in person images. However, the part partition of these methods is also coarse and these methods cannot explicitly locate the semantic parts. Besides, the semantic consistency of the focus area among images is not guaranteed. By contrast, our AAformer can locate the identifiable local parts at the patch-level and guarantee the semantic consistency among images by the proposed [PART]s. Apart from AAformer, identity-guided human semantic parsing (ISP) [4] also proposes to locate both human parts and nonhuman ones automatically by iterative clustering, but their off-line part partition is a little bit time-costing and prevents their method from end-to-end training.

B. **Visual Transformer**

Recently, the transformer [5] is showing its superiority over conventional methods in many vision tasks. ViT [6] proposes the vision transformer to apply a pure transformer to image recognition. They first divide the input image into image patches and then map them to a sequence of vectors with a linear projection. An extra learnable “class token (CLS)” is added to the sequence and the vector sequence is fed to a typical transformer encoder. TransReID [7] proposes to apply ViT to object re-ID. They design patch shuffle operations and introduce side information like camera/view IDs to learn robust features, validating the superiority of the transformer on re-ID task. DCAL [37] proposes to implicitly extract the local features using a transformer decoder. PAT [38] and HAT [39] both integrate transformer architecture into CNNs. PAT proposes to use the transformer to generate the attention masks for CNN and HAT uses the transformer to aggregate hierarchical features from CNN backbones. However, as they do not design an explicit alignment scheme for the transformer, how to extract discriminative part features from person images is still unexplored in transformer architecture. In this article, we aim to propose a specific alignment scheme for the transformer and also alleviate the problems in existing CNN-based alignment methods.

Besides, some methods [40], [41] also design to add learnable tokens to the transformer network. GroupViT [40] uses the Gumbel Softmax function to group the patches to the learnable group tokens, which assign the image patches to their most similar group tokens with a high probability. Compared with GroupViT, AAformer uses OT to assign image patches to [PART]s, which can avoid the trivial solution where all the patches are assigned to the same [PART]. VPT [41] fixes the parameters of a pretrained model and only trains the added learnable token to reduce the number of parameters and calculation cost. The learnable token in VPT still interacts with all the image patches. While in AAformer, a [PART] only interacts with a subset of patch embeddings, thus can learn to be the local representation.

### III. Methodology

In this section, we expound the proposed method in detail. We begin by briefly revisiting the general transformer architecture in Section III-A. Then we present the proposed [PART] and the AAformer in Section III-B step by step.

A. **Main Architecture**

We follow ViT [6] to construct the main architecture. Given an input image \(x \in \mathbb{R}^{H \times W \times C}\) with resolution \((H, W)\) and channel \(C\), we reshape it into a sequence of flattened 2-D patches \(x \in \mathbb{R}^{N \times (I^2)}\) to fit the transformer architecture, where \((I, I)\) is the resolution of each image patch and \(N = (H \cdot W)/I^2\) is the length of image patch sequence. We map the patches to vectors of \(D\) dimensions with a trainable linear projection and refer to the output of this projection as the patch embeddings. A standard embedding of “class token (CLS)” is added to extract the global representation. Lastly, the outcome vector sequence \(Z \in \mathbb{R}^{L \times D}\) is fed to the transformer encoder, where \(L = 1 + N\). We also add the standard learnable 1-D position embeddings to the vector sequence in elementwise to retain positional information.

The standard transformer layer [5] consists of multihead self-attention (MSA) and multilayer perceptron (MLP) blocks. The self-attention mechanism is based on a trainable associative memory with key and value vector pairs. For every query vector in a sequence of query vectors \((Q \in \mathbb{R}^{L \times D})\), we calculate its inner products with a set of key vectors \((K \in \mathbb{R}^{L \times D})\). These inner products are then scaled and normalized with a softmax function to obtain \(L\) weights. The output of the self-attention for this query is the weighted sum of a set of \(L\) value vectors \((V \in \mathbb{R}^{L \times D})\). For all the queries in the
sequence, the output matrix of self-attention can be obtained by

$$\text{Attention}(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{D}} \right) V$$  (1)

where the Softmax function is applied over each row of the input matrix and the $\sqrt{D}$ term provides appropriate normalization. Query, key, and value matrices are all computed from the vector sequence $Z$ using different linear transformations: $Q = ZW_Q$, $K = ZW_K$, $V = ZW_V$. Finally, the multi-head self-attention layer (MSA) is defined by considering $h$ attention “heads,” i.e., $h$ self-attention functions are applied to the input in parallel. Each head provides a sequence of size $L \times d$, where $d = D/h$ typically. The outputs of the $h$ self-attention are rearranged into a $L \times D$ sequence to feed the next transformer layer.

The MSA is followed by a MLP block to build a full transformer layer. This MLP contains two linear layers separated by a GELU nonlinearity [42]. The first linear layer expands the dimension from $D$ to $4D$ and the second reduces the dimension back to $D$. Both MSA and MLP are operating as residual connections and with a layer normalization (LN) [43] before them. We change the MSA layer to multihead auto-alignment (MAA) layer to build our AAFormer. The overview of AAFormer is shown in the left part of Fig. 2.

### B. Auto-Aligned Transformer

1) [PART]s for Transformer: We propose the [PART]s for transformer to extract the part features and integrate the part alignment into self-attention. We concatenate $P$ [PART]s, which are learnable vectors, to the sequence $Z$, thus now the length $L$ of $Z$ is $1 + P + N$. A [PART] only interacts with a subset of patch embeddings, rather than all of them, and thus can learn to be the partial representation of the subset. Specifically, we denote $Q^{PT} = [Q_1^{PT}, \ldots, Q_P^{PT}]$ as the query vectors of [PART]s and denote $\Phi_p$ as the subset of patch embeddings assigned to the $p$th [PART]. For the query vector of the $p$th [PART], denoted as $Q_p^{PT}$, we only calculate its inner products with the key vectors belonging to $\Phi_p$ and then scale and normalize these inner products with softmax function to obtain $\text{len}(\Phi_p)$ weights. The output of the part alignment for $Q_p^{PT}$ is the weighted sum of value vectors belonging to $\Phi_p$, which is formulated as

$$\text{Alignment}(Q_p^{PT}, \Phi) = \text{Softmax} \left( \frac{Q_p^{PT}K_{\Phi}^T}{\sqrt{D}} \right)V_{\Phi}$$  (2)

where $K_{\Phi}$ and $V_{\Phi}$ are the key and value vectors belonging to $\Phi_p$, respectively. After the part alignment, the output vector of [PART] $p$ becomes the part representation of subset $\Phi_p$. The CLS token and patch embeddings are processed by the original self-attention [see (1)].

Now, to extract discriminative part features, the core problem is how to accurately and adaptively assign image patches to $\Phi_p$, $p \in \{1, \ldots, P\}$.

2) Multihead Auto-Alignment: The auto-alignment aims at automatically grouping the image patches into different $\Phi_p$ ($p \in \{1, \ldots, P\}$), in which both human parts and nonhuman ones are included. The $\Phi_p$ for different [PART]s should be mutually exclusive. Our idea is adaptively clustering the patch embeddings into $P$ groups with the [PART]s as their prototypes. This makes the patch assignment problem the same as the OT problem [8]. In detail, the query vectors of [PART]s, $Q^{PT} \in \mathbb{R}^{P \times D}$, are regarded as the part prototypes, and we are interested in mapping the key vectors of image patches $K \in \mathbb{R}^{N \times D}$ to the $Q^{PT}$ to obtain the patch assignment (CLS token does not participate in the clustering and is omitted for simplicity). We denote this mapping by $Y \in \mathbb{R}^{P \times N}$, and the value in position $(p, n)$ denotes the probability of the $n$th image patch belonging to the $p$th [PART]. To maximize the similarity between $K$ and $Q^{PT}$, $Y$ is optimized by

$$\max_{Y \in \mathcal{F}} \text{Tr}(Y^TQ^{PT}K^T) + \epsilon H(Y)$$  (3)
where $\text{Tr}(Y^TQ^PK^T)$ measures the similarity between $K$ and $Q^P$, $\text{Tr}$ means the trace of a matrix, $H(Y) = -\sum_{i,j} Y_{ij} \log Y_{ij}$ is the entropy function, and $\epsilon$ is the parameter that controls the smoothness of the mapping and is set to be 0.05 in our experiments.

To further prevent the trivial solution where all the patches are assigned to the same [PART], we enforce an equal partition by constraining the matrix $Y$ to belong to the transportation polytope [44], [45]. We adapt this constraint to patch assignment by restricting the transportation polytope to the image patches of an image

$$Y = \left\{ Y \in \mathbb{R}^{P \times N}_+ | Y1_N = \frac{1}{P}1_P, Y^T1_P = \frac{1}{N}1_N \right\} \quad (4)$$

where $1_P$ denotes the vector of ones in dimension $P$. These constraints enforce that on average each [PART] is selected at least $N/P$ times in an image. The soft assignment $Y^*$ are the solution to Problem 3 over the set $Y$ and takes the form of a normalized exponential matrix [8]

$$Y^* = \text{Diag}(u) \exp \left( \frac{Q^PK^T}{\epsilon} \right) \text{Diag}(v) \quad (5)$$

where $u$ and $v$ are renormalization vectors in $\mathbb{R}^P$ and $\mathbb{R}^N$, respectively. Diag(*) represents a matrix with * as its diagonal elements. These renormalization vectors are computed using a small number of matrix multiplications by a fast variant of Sinkhorn–Knopp algorithm [8]. This algorithm can be efficiently run on GPU and we observe that only three iterations are sufficient to obtain good performance for patch assignment. In our experiments, grouping 576 patch embeddings of an input image, the output [PART]s only takes 0.46 ms. Once a continuous solution $Y^*$ is found, the patch assignment can be obtained by using a rounding procedure. The patch embeddings mapped to $Q^P$ form the patch subset $\Phi_p$. We illustrate the auto-alignment process (single-head) in the right part of Fig. 2. The auto-alignment is conducted in parallel in different attention heads, which enhances the robustness of patch assignment. We name this MAA and the outputs of different attention heads are concatenated together. The output [PART]s of AAformer are the part representations of the input images and they are instance-adaptive.

C. Objective Function

In the training phase, the re-ID heads [46] are attached to the output CLS and [PART]s of AAformer. Specifically, the output CLS $Z_0$ represents the global feature of the input image, and the output [PART]s $Z_{1:P}$ are the part features. We employ cross-entropy loss and triplet loss with hard sample mining [47] to train our model. The cross-entropy loss is calculated as

$$L_{cls} = \frac{1}{P+1} \sum_{i=0}^{P} - \log P(Z_i) \quad (6)$$

where $P(Z_i)$ is the probability of token $Z_i$ belonging to its ground truth identity. The classifiers of different tokens are not shared. Label smoothing [48] is adopted to improve the performance.

The [PART]s $Z_{1:P}$ are concatenated together to calculate the part triplet loss. Together with the global triplet loss calculated with CLS, there are two terms in the triplet loss

$$L_{trip} = \frac{1}{2} \left[ (d_p^g - d_p^e + \alpha)_+ + (d_p^p - d_p^e + \alpha)_+ \right] \quad (7)$$

where $d_p^g$ and $d_p^e$ are feature distances of global representation (CLS) from positive pair and negative pair, respectively. $d_p^p$ and $d_p^e$ are feature distances of concatenated [PART]s from positive pair and negative pair, respectively. $\alpha$ is the margin of triplet loss and is set to 0.3. $[\cdot]_+$ equals to max$(\cdot, 0)$. The triplet losses are calculated with hard sample mining strategy [47]. Specifically, for each image, the hard sample mining strategy only uses the hardest positive sample (the least similar positive sample) and the hardest negative sample (the most similar negative sample) to form the positive pair and negative pair. In AAformer, the triplet losses for the global feature and part feature are calculated separately. That is, the hardest positive and negative pairs found by global and part features can be different. Therefore, there are two groups of positive and
negative objective pairs for each image in AAformer. Therefore, the overall objective function for our model is

$$L = L_{cls} + L_{wi}. \quad (8)$$

In the testing phase, CLS and [PART]s are concatenated together to represent a person image.

IV. EXPERIMENTS

In this section, we first list the implementation details of the proposed method. Then, we compare the proposed method with the state-of-the-art methods on both holistic and occluded person re-ID benchmark. At last, we conduct the ablation studies including the effectiveness of [PART]s, the effectiveness of AAformer, the comparison between OT and nearest neighbor (NN), and the visualization of AAformer. All these results validate the effectiveness of the proposed method.

A. Implementation Details and Datasets

1) Transformer Architecture: We use the smallest ViT model proposed in [6], ViT-Base, as the main architecture of AAFormer. It contains 12 transformer layers with the hidden size of 768 dimensions ($D = 768$). The MLP size is four times the hidden size and the head number is 12 for multithead operations.  

2) Data preprocessing: The input images are resized to $256 \times 128$ and the patch size is $16 \times 16$. We adopt the commonly used random cropping [49], horizontal flipping, and random erasing [34] (with a probability of 0.5) for data augmentation.  

3) Training: We warm up the model for 10 epochs with a linearly growing learning rate from $8 \times 10^{-4}$ to $8 \times 10^{-3}$. Then, the learning rate is decreased with the cosine learning rate decay. It takes 120 epochs to fine-tune the re-ID datasets. AAFormer randomly samples 16 identities and four images per person to constitute a training batch. The batch size equals to $16 \times 4 = 64$. SGD optimizer is adopted with a momentum of 0.9 and the weight decay of $1 \times 10^{-4}$ to optimize the model. Our methods are implemented on PyTorch and MindSpore. The transformer backbone is pretrained on ImageNet [50].  

4) Datasets and Evaluation Metrics: We conduct experiments on four widely used person re-ID benchmarks, i.e., DukeMTMC-reID [11], Market-1501 [9], CUHK03 (New Protocol) [70], and the large-scale MSMT17 [12]. The standard training/test ID split is used and detailed in Table I. Following common practices, we use the cumulative matching characteristics (CMC) and the mean average precision (mAP) to evaluate the performance. Euclidean distance is used to measure the feature distances.

1The codes based on MindSpore will be released at https://gitee.com/typhoonai/AAformer.

| Dataset            | ID  | Train | Test | Images |
|--------------------|-----|-------|------|--------|
| DukeMTMC-reID      | 1402| 702   | 702  | 36411  |
| Market-1501        | 1501| 751   | 750  | 32668  |
| CUHK03             | 1467| 767   | 700  | 14097  |
| MSMT17             | 4107| 1041  | 3060 | 126441 |

Fig. 4. Ranking lists of TransReID and AAformer in misalignment scenes. Tiny clues are found by our AAFormer.

B. Comparison With State-of-the-Art Methods

We compare our method with the state-of-the-art methods on four widely used holistic benchmarks and one occluded benchmark in Tables II and III. We also show the results of the baseline model (ViT-baseline [6]) in the tables. We follow BoT [46], a popular baseline method in person ReID filed, to form the ViT-baseline. Most of the settings refer to BoT, including the warmup learning rate, random erasing augmentation [34], label smoothing [48], and BNNeck [46].  

1) DukeMTMC-reID: AAFormer obtains the best results and outperforms others by considerable margins, e.g., at least 0.5% on Rank-1 accuracy and 0.8% on mAP accuracy. The compared methods are categorized into four groups, i.e., stripe-based methods, bounding box-based methods, extra semantics-based methods, and others. The others include the general attention methods based on CNN [36], [59], the work that combines self-attention with CNN [38], [58] and the method based on generative adversarial network [61]. AAFormer surpasses all the above methods by considerable margins, which validates the superiority of locating both human parts and nonhuman ones.

2) Market1501: AAFormer achieves state-of-the-art performance. Specifically, AAFormer obtains the second-best results and is only slightly behind the firsts [67]. As the performance on this dataset is nearly saturated, the results of sate-of-the-art methods are very close.

3) CUHK03: AAFormer obtains the best performance on both labeled and detected sets. More specifically, AAFormer outperforms the second-best algorithms [7], [60] by 1.4%/2.1% and 1.9%/4.0% on labeled and detected sets with regards to Rank-1 and mAP, respectively. Compared with ISP [4], which is a CNN-based method that also conducts adaptive part alignment, AAFormer obtains much better performance on this difficult dataset. We owe this to our online clustering, which can be more accurate than the off-line clustering in ISP. AAFormer also significantly surpasses the ViT-baseline by 4.1%–5.6%, which validates the effectiveness of MAA.
TABLE II
COMPARISON WITH THE STATE-OF-THE-ART METHODS FOR THE HOLISTIC PERSON RE-ID PROBLEM. METHODS IN THE FIRST GROUP ARE THE STRIPE-BASED METHODS. METHODS IN THE SECOND GROUP ARE BOUNDING BOX-BASED METHODS. METHODS IN THE THIRD GROUP ARE EXTRA SEMANICS-BASED METHODS. METHODS IN THE FOURTH GROUP INCLUDE THE GENERAL ATTENTION METHODS OF CNN [36], [59], THE WORK THAT COMBINES SELF-ATTENTION WITH CNN [38], [58] AND THE METHOD BASED ON PURE TRANSFORMER [7], [37]. TRANSReID” MEANS THE SIDE INFORMATION IS REMOVED FOR A FAIR COMPARISON.

| Methods   | Ref       | DuketMTCMC -reID | Market1501 | CUHK03 Labeled | CUHK03 Detected | MSMT17 Rank-1 mAP | MSMT17 Rank-1 mAP |
|-----------|-----------|------------------|------------|----------------|-----------------|-------------------|------------------|
| AlignedReID [51] | Arxiv18 | 91.8 | 79.3 | - | - | - | - |
| PCB+RPP [1] | ECCV18 | 83.3 | 69.2 | 93.8 | 81.6 | - | - |
| MGNet [3] | MM18 | 88.7 | 78.4 | 95.7 | 86.9 | - | - |
| MSCAN [24] | CVPR17 | - | - | 80.8 | 57.5 | - | - |
| PAR [26] | ICCV17 | - | - | 81.0 | 63.4 | - | - |
| SPReID [2] | CVPR18 | 84.4 | 71.0 | 92.5 | 81.3 | - | - |
| PABR [52] | ECCV18 | 84.4 | 69.3 | 91.7 | 79.6 | - | - |
| AA Net [53] | CVPR19 | 87.7 | 74.3 | 93.9 | 83.4 | - | - |
| F²-Net [54] | ICCV19 | 86.5 | 73.1 | 95.2 | 85.6 | 78.3 | 73.6 | 74.9 | 68.9 | - | - |
| PGFA [55] | ICCV19 | 82.6 | 65.5 | 91.2 | 76.8 | - | - |
| CDPM [29] | TIP19 | 88.2 | 77.5 | 95.2 | 86.0 | 75.8 | 71.1 | 71.9 | 67.0 | - | - |
| GASM [56] | ECCV20 | 88.3 | 74.4 | 95.3 | 84.7 | - | - |
| PGFA_v2 [57] | TNNLS21 | 86.2 | 73.6 | 92.7 | 81.3 | - | - |
| Non-Local [58] | CVPR18 | 86.6 | 78.7 | 94.9 | 86.8 | 66.4 | 65.0 | 65.3 | 63.1 | 76.2 | 53.3 |
| LANet [59] | CVPR19 | 87.1 | 73.4 | 94.4 | 83.1 | - | - |
| CASN-PCB [16] | CVPR19 | 87.7 | 73.7 | 94.4 | 82.8 | 73.7 | 68.0 | 71.5 | 64.4 | 79.5 | 56.8 |
| BAT-net [60] | ICCV19 | 87.7 | 77.3 | 95.1 | 84.7 | 78.6 | 76.1 | 76.2 | 73.2 | 79.5 | 56.8 |
| JDGL [61] | CVPR19 | 86.6 | 74.8 | 94.8 | 86.0 | - | - |
| OSNet [62] | ICCV19 | 88.6 | 73.5 | 94.8 | 84.9 | - | - |
| CL-CNN [63] | TIP19 | 86.7 | 81.3 | 94.2 | 83.9 | - | - |
| OCLSM [64] | TIP20 | 87.7 | 79.0 | 94.6 | 87.4 | - | - |
| ISP [45] | ECCV20 | 89.6 | 80.0 | 95.3 | 88.6 | 76.5 | 74.1 | 75.2 | 71.4 | - | - |
| PAT [38] | CVPR18 | 88.8 | 78.2 | 95.4 | 85.0 | - | - |
| PFE [65] | TIP21 | 88.2 | 75.9 | 95.1 | 86.2 | - | - |
| FA-Net [66] | TIP21 | 88.7 | 77.0 | 95.0 | 84.6 | - | - |
| HORI-DeF [67] | TIP21 | 88.1 | 79.8 | 95.7 | 88.7 | - | - |
| TransReID + [7] | ICCV21 | 89.6 | 79.8 | 94.2 | 87.7 | 78.9 | 76.9 | 75.1 | 72.9 | 82.5 | 63.6 |
| reID-NAS [68] | TNNLS21 | 88.1 | 74.6 | 95.1 | 85.7 | - | - |
| MBSSN-Net [59] | TNNLS22 | 87.3 | 73.1 | 94.6 | 84.0 | 75.6 | 72.7 | 72.8 | 69.3 | - | - |
| DCAL [37] | CVPR22 | 89.0 | 80.1 | 94.7 | 87.5 | - | - |
| ViT-baseline | - | 88.3 | 78.5 | 94.2 | 86.3 | 73.3 | 74.9 | 74.0 | 71.6 | 79.7 | 58.9 |
| AAllformer (ours) | this paper | 90.1 | 80.9 | 95.4 | 88.0 | 80.3 | 79.0 | 78.1 | 77.2 | 84.4 | 65.6 |

Fig. 5. Attention map of [PART] (PT). For one [PART], the patches not assigned to it are masked by black. The color range from blue to red indicates increasing attention.

4) MSMT17: On the largest dataset, AAllformer also outperforms the state-of-the-art results. On the metric of Rank-1, AAllformer outperforms the second-best [7] by 1.3%. On the metric of mAP, AAllformer outperforms the second-best [7] by 1.6%. It should be noted that we remove the side information in [7] for a fair comparison. Besides, we strongly recommend not using side information like camera IDs. Because if the camera IDs are used, the trained model can not be applied to
other monitoring systems as the cameras are different, which largely limits the generality and practicability.

5) Occluded-DukeMTMC: AAformer sets the new state-of-the-art performance and outperforms others by a large margin, at least 2.6%/4.6% in Rank-1/mAP. Owing to the Auto-Alignment, the [PART]s can adaptively focus on the visible areas in the occluded images and extract discriminative features from these visible areas. We also visualize the attention maps of [PART]s in the ablation studies to validate this.

C. Ablation Studies

1) Effectiveness of the [PART]s: We first conduct experiments to validate the effectiveness of [PART]s. We begin by naively adopting the alignment paradigm of CNNs, i.e., part masks with part pooling, to the baseline transformer model (ViT-Base). Three typical methods, i.e., PCB, MGN, and SPReID, are used for this experiment. The first two methods are stripe-based methods and the third method adopts the extra semantics. As shown in Table IV, naively applying the alignment paradigm of CNNs even reduces the performance of the baseline model, which may be because pooling is not suitable for transformer-based person re-ID. Next, we discard the pooling operation and add the proposed [PART]s to ViT to extract part features. These typical CNN-based methods are easily transferred to the transformer by our [PART]s, e.g., we assign each [PART] with patches within a stripe to simulate the image partition of PCB and divide the image patches according to a pretrained human parsing model to simulate SPReID. Specifically, in the simulation experiment of SPReID, if a patch contains multiple body parts. Thanks to the flexibility of AAformer, we can partition the input image with different granularity in parallel and correspond to the consistent [PART]s. A naive alternative algorithm is the NN, which assigns the patch embedding to the nearest [PART]. Unfortunately, in our experiments, we observe that most patch embeddings are grouped to the nearest [PART] when adopting NN as there is no constraint on the patch assignment. The results in Table V also demonstrate the superiority of OT over NN.

2) Effectiveness of AAformer: As shown in the last row of Table IV, AAformer surpasses all the typical alignment methods reimplemented on [PART]s by large margins, e.g., AAformer outperforms [PART]s with MGN’s partitioning by 1.9%/2.2% in terms of Rank-1/mAP on MSMT17, which validates the superiority of online adaptive patch assignment over the fixed patterns. Besides, to validate the strong ability of AAformer in finding the tiny clues in the misalignment scenes, we compare the ranking list between TransReID [7] and AAformer in Fig. 4. As shown, AAformer can find the discriminative tiny clues from both human parts and nonhuman ones, while TransReID fails at this due to the lacking of an alignment scheme.

3) Optimal Transport Versus Nearest Neighbor: Most other clustering methods (K-means, DBSCAN) cannot be used for adaptive patch assignment, because they cannot guarantee the grouped clusters of different images (or the clusters of the same image from different layers) have the same semantics and correspond to the consistent [PART]s. A naive alternative algorithm is the NN, which assigns the patch embedding to the nearest [PART]. Unfortunately, in our experiments, we observe that most patch embeddings are grouped to the same [PART] when adopting NN as there is no constraint on the patch assignment. The results in Table V also demonstrate the superiority of OT over NN.

4) Different Numbers of [PART]s: Intuitively, the number of [PART]s P determines the granularity of the body parts. Thanks to the flexibility of AAformer, we can partition the input image with different granularity in parallel in an AAformer model. For example, granularity [2, 3] indicates there are five [PART]s added. The first two [PART]s divide the image patches into two groups and the last three [PART]s divide them into three. All the [PART]s are randomly and independently initialized, but they will be assigned image

Other monitoring systems as the cameras are different, which largely limits the generality and practicability.

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Besides, to prove the improvement is not brought by the increase of feature dimension, we conduct the experiment which directly adds more CLS tokens to ViT. The results in Table IV validate that naively increasing the feature dimension only slightly improves the performance as the information contained in these CLS tokens is similar and redundant.

2) Effectiveness of AAformer: As shown in the last row of Table IV, AAformer surpasses all the typical alignment methods reimplemented on [PART]s by large margins, e.g., AAformer outperforms [PART]s with MGN’s partitioning by 1.9%/2.2% in terms of Rank-1/mAP on MSMT17, which validates the superiority of online adaptive patch assignment over the fixed patterns. Besides, to validate the strong ability of AAformer in finding the tiny clues in the misalignment scenes, we compare the ranking list between TransReID [7] and AAformer in Fig. 4. As shown, AAformer can find the discriminative tiny clues from both human parts and nonhuman ones, while TransReID fails at this due to the lacking of an alignment scheme.

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4) Different Numbers of [PART]s: Intuitively, the number of [PART]s P determines the granularity of the body parts. Thanks to the flexibility of AAformer, we can partition the input image with different granularity in parallel in an AAformer model. For example, granularity [2, 3] indicates there are five [PART]s added. The first two [PART]s divide the image patches into two groups and the last three [PART]s divide them into three. All the [PART]s are randomly and independently initialized, but they will be assigned image
patches of different semantics in the training, and eventually learn to be different part prototypes. The results of AAFormer with different numbers of [PART]s are shown in Table VI. As we can observe, the setting of [2, 3] usually obtains the best accuracy, which is consistent with the setting of MGN. Besides, the results also show that the number of [PART]s is not the more the better. All the previous results are obtained with the default setting of granularity [2, 3].

5) Visualization of AAFormer: Lastly, we conduct visualization experiments to show the focusing areas of [PART]s. We visualize the attention map of [PART]s in the first head of the third transformer layer, which is shown in Fig. 5. As we can observe, AAFormer can focus on both human parts and non-human ones, which are both crucial for re-ID. This is also the main superiority of AAFormer over existing methods. Besides, we can also find that AAFormer can effectively handle the pose variation and the occlusion problems. Owing to the self-attention mechanism, the [PART]s have very low responses to the background patches, thus it is no need for AAFormer to remove the background patches. The visualization also proves the semantics consistency of the located parts among images.

V. Conclusion

In this article, we propose the [PART]s for the transformer to extract the part-level features. We propose to integrate the part localization process into the self-attention of the transformer to online learn the part representations. The proposed method, AAFormer, can adaptively locate both human parts and non-human ones using OT without the help of extra semantics. It should be noted that most other clustering methods (k-means, DBSCAN) cannot be used in AAFormer, because they cannot guarantee that the grouped clusters of different images (or the same image from different layers) are of identical semantics and correspond to the consistent [PART]s. It is our novel design of AAFormer that makes it possible to use OT to solve the adaptive alignment problem. Extensive experiments also validate the effectiveness of [PART]s and the superiority of AAFormer over lots of state-of-the-art methods.

TABLE VI

| P | MSMT17 Rank-1 | MSMT17 mAP | CUHK03(L) Rank-1 | CUHK03(L) mAP |
|---|---|---|---|---|
| [4] | 82.4 | 62.3 | 78.5 | 79.9 |
| [5] | 82.0 | 61.6 | 79.8 | 78.2 |
| {6} | 81.7 | 61.4 | 79.2 | 77.3 |
| [2, 3] | 84.4 | 65.6 | 80.3 | 79.0 |
| [3, 4] | 83.1 | 63.2 | 79.4 | 78.0 |
| [2, 3, 4] | 82.9 | 63.0 | 78.8 | 77.6 |

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