# Disentangling Identity from Clothing: A Semantically-Supervised Decoupling Framework for Robust Person Re-Identification

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## Abstract

*Text-to-Image Person Re-Identification is critically hampered by the difficulty of fine-grained semantic alignment, as retrieval accuracy is degraded by clothing-induced interference and a persistent modality gap. In this paper, we propose a novel framework to resolve this issue, centered on feature decoupling guided by a Multimodal Large Language Model (MLLM). Our framework introduces two core components: a Bidirectional Decoupling Alignment Module and a Mamba State Space Model (SSM) for efficient fusion. To obtain high-quality, fine-grained supervision, we first employ MLLM to automatically generate separate identity and clothing descriptions. These descriptions then guide our decoupling module, which utilizes bidirectional attention and a gated weighting strategy to meticulously disentangle visual features into identity and clothing subspaces. To enforce this separation and ensure identity purity, we design a multi-task loss strategy comprising an adversarial loss that actively suppresses the influence of clothing-related features, and a kernel-based orthogonal constraint that ensures statistical independence. Furthermore, we pioneer the integration of the Mamba SSM into cross-modal Re-ID as an efficient fusion module. By leveraging its linear-time complexity and proficiency in modeling long-range dependencies, it facilitates deep contextual interactions across modalities while avoiding the quadratic complexity of Transformers. Comprehensive experiments on multiple benchmark datasets reveal that our proposed method achieves superior performance compared to leading contemporary methods, proving its effectiveness and robustness.*

**Keywords:** Multimodal Learning, Text-to-Image Re-Identification, Feature Decoupling, Semantic Supervision.
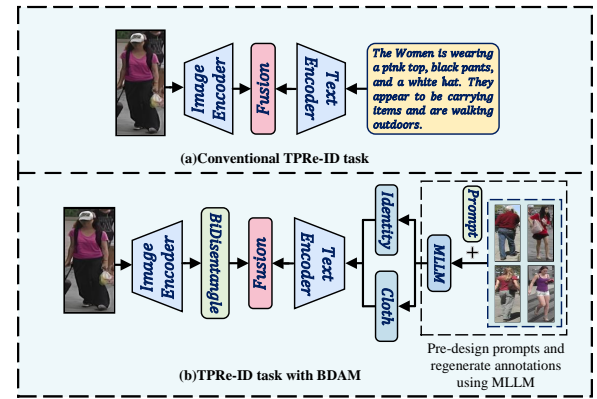


Figure 1. Comparison of ReID methods.(a) Traditional: Direct fusion of image and text features without distinguishing identity from non-identity information limits alignment.(b) Proposed (BDAM): Introduces a decoupling module that aligns separated identity/clothing features with MLLM-generated descriptions for fine-grained matching.

## 1. Introduction

Text-to-Image Person Re-Identificatio (T2I-ReID) retrieves a target pedestrian from a large-scale image gallery given a natural-language description [7, 15, 31, 40]. It is valuable for video surveillance [3], intelligent security [10], public safety, and social media. Despite recent progress, practical deployment remains challenging: image factors (pose, viewpoint, illumination) obscure identity-relevant cues, and a persistent modality gap hampers effective fusion in a shared space. These issues are exacerbated at the fine-grained level, where semantic alignment is particularly difficult.

A core challenge in T2I-ReID is the semantic gap between images and text. Early work attempted to reduce this discrepancy by projecting global visual and textual features

into a shared space [19, 34, 36], but high intra-class variance and low inter-class variance across both modalities hinder reliable cross-modal matching. To overcome this, subsequent studies introduced feature disentanglement, broadly via explicit or implicit alignment [12, 38]. Explicit methods [7, 37] detect body parts or attributes and align local regions and phrases with auxiliary modules. Implicit methods [15, 31] avoid external tools and use regularizers to associate noun phrases with image regions. This progression demonstrates that distinguishing identity-relevant from identity-irrelevant semantics is essential; therefore, disentanglement has become a key avenue to advance T2I-ReID.

This pursuit of disentanglement has been propelled by powerful backbones. Models employing ViT [8, 14, 21, 33, 42, 47] excel at capturing fine-grained visual details, while methods leveraging CLIP [26, 28, 43] utilize large-scale pretraining to learn a well-aligned joint embedding space. These architectures, often paired with cross-attention, have significantly advanced the state-of-the-art in cross-modal alignment. Despite this progress, a critical limitation persists. Both lines of work commonly treat the textual description holistically. This approach overlooks the semantic distinction between content relevant to identity (e.g., gender, body shape) and content irrelevant to identity (e.g., clothing, hairstyle). In complex scenes, this coarse-grained treatment forces the model to entangle these factors, often prioritizing salient but non-essential clothing details over stable identity cues. This ambiguity blurs identity features, weakens the decoupling process, and ultimately degrades matching robustness.

To address this challenge, we propose a novel framework that moves beyond such holistic feature treatment by introducing explicit, fine-grained semantic supervision. Inspired by the style-clustering paradigm [16], our approach employs MLLM to guide feature decoupling. This is achieved by automatically generating fine-grained, distinct, and mutually exclusive descriptions for both identity and clothing. These decoupled annotations provide the precise supervision for our BDAM to meticulously separate and align identity and clothing information. This disentanglement is enforced by a multi-task loss strategy, including an adversarial loss and an orthogonality constraint based on HSIC, as detailed in our Sec. 3. Furthermore, to enhance alignment, we pioneer the integration of the Mamba SSM as an efficient fusion module, adept at capturing long-range cross-modal dependencies with linear complexity.

Our main contributions are threefold: (1) An automatic prompt construction pipeline that combines style clustering with an MLLM to produce fine-grained, decoupled identity and clothing descriptions; (2) The BDAM, which achieves precise decoupling and alignment reinforced by a multi-task

loss strategy combining an adversarial loss and an orthogonality constraint based on HSIC; and (3) The novel integration of a Mamba SSM fusion module that models long-range cross-modal dependencies with linear complexity.

## 2. Related Work

### 2.1. Feature Disentanglement

Feature disentanglement [35] aims to separate semantically distinct factors in feature space to improve interpret ability and generalization. Early approaches often leveraged generative models (VAEs, GANs)[23] to partition latent codes into structured factors. More recently, disentanglement has expanded beyond generation to image classification[29], NLP [5], and multimodal learning [25]. Mainstream strategies include minimax multi-task adversarial training that jointly optimizes an encoder and a style discriminator [23]; schemes based on metric learning such as DFR [4] with a Gradient Reversal Layer [11] to decorrelate factors; and orthogonal linear projections that separate visual and textual embeddings under CLIP [25].

In the ReID domain, disentanglement typically separates identity-relevant signals from nuisances [1, 22]. Generative designs model these factors independently. In vehicle Re-ID, DFLNet[2] jointly extracts orientation-specific and generic features. For occlusion, ProFD [6] uses text prompts to isolate body-part features. Re-ID focused on clothing changes often adopts dual-stream architectures to counter appearance shifts and camera bias [22].

While these efforts improve semantic purity and factor independence, two critical limitations persist. First, without an effective interaction mechanism, isolated factors may fail to support robust cross-modal matching, leading to brittle alignment. Second, reliance on manual annotations or external detectors constrains scalability and domain transfer. Furthermore, implicit regularizers can be underconstrained, yielding spurious separations on unseen data. Consequently, recent work emphasizes coupling disentanglement with principled interactions and independence constraints. In this spirit, our framework pairs decoupling at the data level with model-level disentanglement and independence enforcement, providing explicit supervision and controllable separation while preserving cross-modal synergy.

### 2.2. Feature Fusion

Feature fusion is central to T2I-ReID, with most methods relying on Transformers or CLIP [30]. Cross-modal modules built on multi-head attention process image and text tokens in parallel to capture semantic associations [44], but their quadratic complexity in sequence length causes mem-

ory and latency spikes for high-resolution images or long descriptions. Pipelines built upon CLIP [17] benefit from large-scale contrastive pretraining and well-aligned embeddings, yet global pooling and holistic processing often blur identity versus clothing cues. This leads to semantic confusion under clothing changes or verbose descriptions. Dynamic fusion that reweights modalities via attention can improve adaptivity [9], but introduces higher computational cost, tuning sensitivity, and performance instability across datasets. Graph-based fusion models [18] dependencies through GNNs, offering relational inductive bias. However, assumptions about graph structure and stationarity limit adaptability to free-form text and dynamic visual contexts.

Contemporary evidence suggests that accuracy and robustness improve only when semantic disentanglement and efficient fusion advance in tandem. Practically, an ideal fusion module should respect factorized semantics, such as identity and clothing, to avoid re-coupling nuisances. It must also capture long-range cross-modal dependencies and scale with linear or near-linear complexity to handle long sequences and high-resolution tokens. This motivates our design: BDAM supplies factor-aware representations and decoupled supervision, while a Mamba SSM fusion module models long-horizon interactions with linear complexity, enabling precise alignment without the memory and efficiency bottlenecks of standard Transformers.

## 3. Method

### 3.1. Overview

To learn pedestrian representations robust to variations in clothing, pose, and environment, this paper proposes the BDAM. This module disentangles and extracts robust features via contrastive and supervised learning, guided by encoded textual features. As illustrated in Fig. 2, our framework comprises two primary feature extraction modules for vision and text, our core BDAM, and an efficient Mamba SSM Fusion Module.

Specifically, given a pedestrian image $I \in \mathbb{R}^{B \times C \times H \times W}$, a visual encoder first extracts image features $f_i$. To obtain semantic guidance, we use an MLLM with pre-designed prompts to generate corresponding descriptions for identity and clothing. A text encoder subsequently encodes these into $f_{id}^t$ and $f_{clo}^t$. During disentanglement, BDAM leverages these textual features to guide the image feature learning process. To ensure the quality of this separation, we introduce a loss based on HSIC to constrain the two resulting feature types towards orthogonality. We also employ an adversarial clothing loss, denoted as $\mathcal{L}_{adv}$, to actively suppress features related to clothing and ensure they do not interfere with identity recognition. Finally, to achieve a deep fusion of visual identity and textual semantics, we introduce the Mamba SSM as a fusion module. It dynamically models and facilitates interaction among the disentangled multimodal features, enhancing the model's overall representation capability.

### 3.2. Bidirectional Decoupled Alignment Module

Some studies directly adopt CLIP [28] as a feature extractor for both modalities, aligning global embeddings for retrieval or discrimination. However, this approach presents two key limitations. First, its limited capacity for fine-grained semantics hinders the separation of identity from clothing. Second, its holistic encoding of images and text lacks the modeling of cross-modal structure at the token level, which reduces robustness in complex scenes.

In this paper, we use a pre-trained ViT (ViT-B/16) as the visual encoder $E_v$ [8]. Given an image $I_i$, $E_v$ outputs token features $f_i \in \mathbb{R}^{B \times L \times D}$ that entangle cues relevant to identity and cues irrelevant to identity. A linear projection with two branches then yields preliminary identity features $f'_{id} \in \mathbb{R}^{B \times L \times D}$ and clothing features $f'_{clo} \in \mathbb{R}^{B \times L \times D}$. These are followed by multi-layer self-attention in each branch to enhance local consistency and contextual awareness.

Instead of using the ViT [CLS] token as a global descriptor, we exploit the full patch sequence and introduce cross-attention between the branches to exchange information. In the identity branch, the clothing branch provides auxiliary context, and vice versa, reinforcing semantic distinctions. Each branch then applies global average pooling to produce $\hat{f}id$ and $\hat{f}clo$. To enable soft disentanglement that is adaptive to the input, we design a gating mechanism. The two global vectors are concatenated and fed to a lightweight linear network with a Sigmoid output, producing a gate $g \in \mathbb{R}^{B \times D}$. We obtain gated features $f_{id}^{gate} = g \odot \hat{f}_{id}$ and $f_{clo}^{gate} = (1 - g) \odot \hat{f}_{clo}$, where $\odot$ denotes element-wise multiplication. This weighting at the dimension level provides a fine degree of control; $f_{id}^{gate}$ is further sent to the fusion module.

To train BDAM and enforce separation, we introduce two specialized loss functions. The first is a clothing adversarial loss, and the second is a decoupling loss based on HSIC to enforce independence between identity and clothing. The clothing adversarial loss suppresses correlations between visual clothing features and clothing text, enhancing the purity of identity features:

$$\mathcal{L}_{adv} = \mathbb{E}_i \left[ -\log(1 - P_{pos}(i)) \right] \tag{1}$$

where $P_{pos}(i)$ is the dot-product similarity, scaled by temperature, between $\hat{f}_{clo}$ and $f_{clo}^t$. In practice, clothing features are linearly projected to the text dimension and normalized
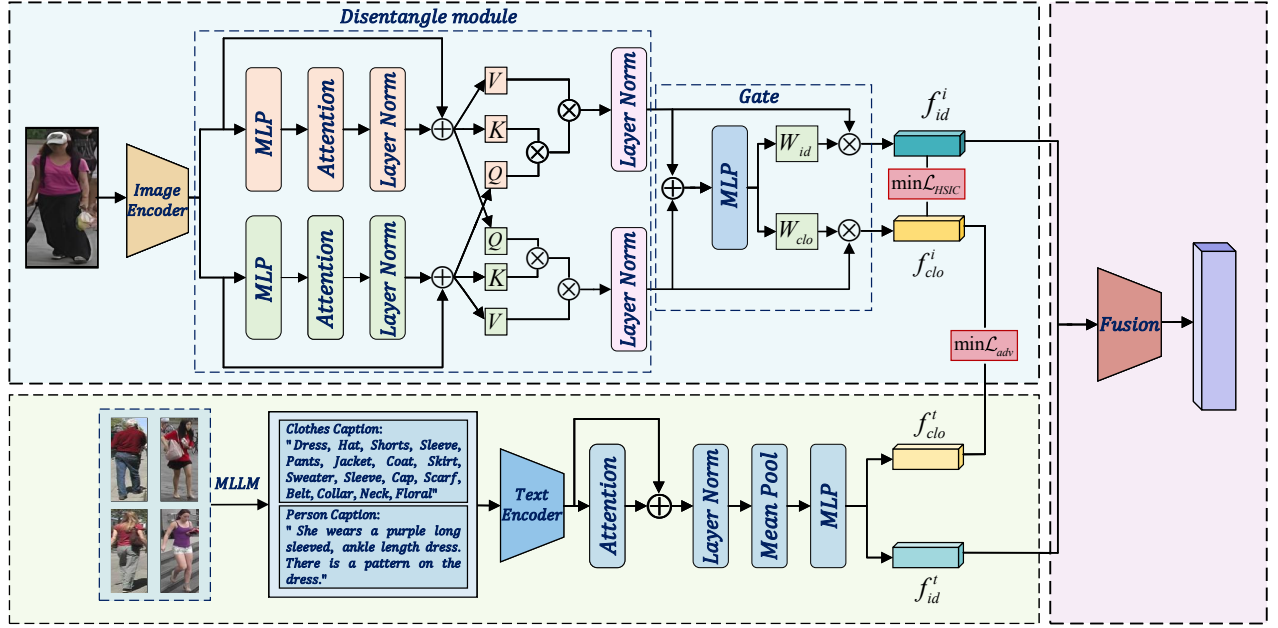
Figure 2. First, we use an MLLM with predefined prompts to generate identity-related and clothing-related descriptions from the pedestrian image, which are encoded as $f_{clo}^t$ and $f_{id}^t$, respectively. Then, the input pedestrian image is encoded into a visual feature $f_i$, which still resides in an entangled feature space. Subsequently, the BDAM module, composed of a dual-branch attention mechanism, decouples $f_i$ into identity feature $f_{id}$ and non-identity feature $f_{clo}$. The decoupling process is supervised and optimized through disentanglement loss and corresponding textual descriptions via contrastive learning. Finally, the fusion module integrates $f_{id}$ and $f_{id}^t$ to generate the final fused feature representation.

using L2 for stable similarity estimation. This adversarial objective explicitly downweights clothing, while the cross-attention mechanism described earlier implicitly sharpens the separation via interaction.

To further encourage statistical independence, we minimize a decoupling loss based on HSIC:

$$
\begin{aligned}
\mathcal{L}_{\text{Decouple}} &= \text{HSIC}(f_{\text{id}}^{\text{gate}}, f_{\text{clo}}^{\text{gate}}) \\
&= \frac{1}{(N-1)^2} \text{tr}(K_{\text{id}} H K_{\text{clo}} H)
\end{aligned}
\tag{2}
$$

Here, $f_{\text{id}}^{\text{gate}} \in \mathbb{R}^{B \times D}$ and $f_{\text{clo}}^{\text{gate}} \in \mathbb{R}^{B \times D}$ are the gated identity and clothing features, respectively. $K_{\text{id}} = f_{\text{id}}^{\text{gate}}(f_{\text{id}}^{\text{gate}})^T$ and $K_{\text{clo}} = f_{\text{clo}}^{\text{gate}}(f_{\text{clo}}^{\text{gate}})^T$ are their respective kernel matrices. $H = I_N - (1/N)\mathbf{1}_N \mathbf{1}_N^T$ is the centering matrix, where $I_N$ is the $N$-dimensional identity matrix and $\mathbf{1}_N$ is a column vector of all ones. HSIC measures the statistical dependence between features by calculating the mean trace of the product of their kernel matrices and the centering matrix. By minimizing this value, the loss encourages the features to be statistically independent.

## 3.3. Semantic enhancement

We employ an MLLM, as detailed in Section 4.2, to automatically generate fine-grained identity and clothing descriptions for pedestrians. This approach reduces the burden of manual annotation and enriches the available supervision. Prior work, notably HAM [16], shows that modeling annotator styles can steer an MLLM to produce diverse texts. Adapting this core insight, we extend the pipeline to meet our model's design goals.

We first use the CLIP text encoder to embed the original descriptions into vectors of a fixed dimension. Using prompts, an MLLM generalizes and substitutes entity attributes to emphasize expression style rather than content. We then cluster these style embeddings with DBSCAN [13], which adaptively discovers dense regions without predefining the cluster count. To stabilize the clusters, we reassign noise points and merge small clusters. This setup aligns the learned style categories with the identity and clothing disentanglement expected by BDAM.

A dual prompt generator guides the MLLM to output two distinct texts per image: one description for identity, covering biological traits, and another for clothing, detailing

apparel, colors, and patterns. We control the generation process with length and temperature constraints. We also apply syntax checks and validation for attribute coverage to ensure the outputs remain grammatical, structured, and parsable.

In summary, our adaptations deliver flexible style modeling via DBSCAN and a decoupled dual description mechanism. This process strengthens the distinctiveness and diversity of identity and clothing semantics. The resulting supervision improves data expressiveness and provides richer training signals for BDAM.

## 3.4. Feature Fusion

For efficient feature fusion that is sensitive to semantics, we introduce the Mamba SSM. The core objective is to preserve the semantic integrity of the purified identity features from both image and text, enabling a fusion that is robust to clothing variations previously isolated by the BDAM. The process begins with an MLP performing dimensional alignment to mitigate distributional discrepancies between modalities. It processes the decoupled visual features $f_{\text{id}}^{\text{gate}}$ and the textual features $f_{\text{id}}^{t}$ to generate aligned features, $f_{\text{img}}$ and $f_{\text{txt}}$. Notably, the decoupled visual clothing feature $f_{\text{clo}}^{\text{gate}}$ is *intentionally discarded* during fusion. This design is central to our goal: the BDAM, supervised by $\mathcal{L}_{\text{adv}}$ and $\mathcal{L}_{\text{Decouple}}$, is tasked with purging information irrelevant to identity into $f_{\text{clo}}^{\text{gate}}$. By excluding this feature from the final fusion, the model is forced to learn a representation based purely on stable identity semantics.

Following this alignment, a gating mechanism achieves dynamic weighted fusion. It outputs a weight vector $w \in \mathbb{R}^{B \times 2}$, which is normalized via a SoftMax layer to produce image $w_1$ and text $w_2$ weights, satisfying $w_1 + w_2 = 1$. The resulting fusion is computed as: $f_{\text{fusion}} = w_1 \cdot f_{\text{img}} + w_2 \cdot f_{\text{txt}}$. This mechanism allows the model to adaptively balance modal contributions based on context. This fusion gate is distinct from the one in the disentanglement module; it outputs a global, two-dimensional weight vector $w \in \mathbb{R}^{B \times 2}$ for the modalities, whereas the disentanglement gate provides a vector $g \in \mathbb{R}^{B \times D}$ for feature control at the dimension level. The resulting $f_{\text{fusion}}$ features are then processed by the Mamba SSM to enhance interaction between modalities. Leveraging its capability to model dependencies over long ranges, Mamba effectively captures complex sequential relationships. We employ a stack of Mamba layers, where each layer updates its input $f_{fusion}^{(l)}$ using a residual connection: $f_{fusion}^{(l+1)} = \text{Mamba}(f_{fusion}^{(l)}) + f_{fusion}^{(l)}$. This structure mitigates the vanishing gradient problem and improves information flow. Finally, the output from the last Mamba layer is projected to produce the final representation, $f_{final} \in \mathbb{R}^{B \times D_{out}}$. The resulting feature is highly adaptive

in its modal weighting and benefits from Mamba's semantic modeling, providing robust support for downstream tasks like person re-identification.

## 3.5. Loss Function

To achieve alignment between modalities at a fine-grained level, we adopt the InfoNCE loss. This loss maximizes similarity for positive image and text pairs (representing the same identity) while separating negatives. It is defined as:

$$\mathcal{L}_{\text{info}} = -\log \frac{\exp(\mathbf{v}^\top \mathbf{t} i / \tau)}{\sum_j \exp(\mathbf{v}^\top \mathbf{t} j / \tau)} \qquad (3)$$

Here, $v_i$ is the image identity feature from the visual encoder, normalized using the L2 norm; $t_i$ is the text feature for the $i$-th identity; and $\tau$ controls distribution sharpness. Negatives within the batch help reduce the semantic gap between modalities and promote alignment in a shared space.

To enhance identity discrimination within a single modality, we include a triplet loss. This loss enforces compactness within classes and separation between classes:

$$\mathcal{L}_{\text{triplet}} = \mathbb{E}(a, p, n) \left[ \max \left( |f_a - f_p|2^2 - |f_a - f_n|2^2 + m, 0 \right) \right] \qquad (4)$$

Here, $(a, p, n)$ represent the identity features of the anchor, positive, and negative samples, respectively; $|| \cdot ||_2$ denotes the L2 norm; and $m$ is the margin parameter used to enforce a minimum distance gap between positive and negative pairs.

In training with multiple tasks, differing loss scales can cause one task to dominate. We adopt GradNorm to balance the training process by dynamically adjusting the gradient norm of each task:

$$\mathcal{L}_{\text{GradNorm}} = \sum_k |\nabla\theta(w_k \mathcal{L}_k) - \tilde{r}kG\text{ref}| \qquad (5)$$

Here, $\nabla\theta(w_k \mathcal{L}k)$ represents the gradient of the weighted loss of task $k$, $w_k \mathcal{L}_k$, with respect to the shared parameters $\theta$. The term $|| \cdot ||_1$ denotes the L1 norm, which emphasizes a linear penalty on the deviation. $\tilde{r}_k = (\mathcal{L}_k/\mathcal{L}_k^0)/\bar{r}$ is the normalized loss ratio, where $\mathcal{L}_k^0$ is the initial loss of task $k$ at the start of training, serving as a baseline, and $\bar{r}$ is the average of the loss ratios over all tasks. $G_{\text{ref}}$ is a reference gradient norm, typically set to the gradient norm of the first task, $||\nabla\theta(w_1\mathcal{L}1)||$.

This mechanism enforces a gradient balance among tasks during training by minimizing the L1 deviation between the actual gradient norm and a target value, $\tilde{r}_k G_{ref}$. Furthermore, to prevent instability caused by the abnormal scaling of task weights $w_k$, we add a regularization term, $\lambda \sum_k (\log w_k)^2$, to the total loss. This term effectively suppresses large discrepancies among the task weights by penalizing the square of their logarithms, thereby improving

training stability. Finally, the overall loss function is defined as follows:

$$\mathcal{L}_{\text{Total}} = \sum_k w_k \mathcal{L}_k + \alpha \mathcal{L}_{\text{GradNorm}} + \lambda \sum_k (\log w_k)^2 \quad (6)$$

Here, $\mathcal{L}_k$ represents the loss term for task $k$ (which includes $\mathcal{L}_{\text{info}}$, $\mathcal{L}_{\text{triplet}}$, $\mathcal{L}_{\text{adv}}$, and $\mathcal{L}_{\text{Decouple}}$), and $w_k = \exp(s_k)$ is the task weight, which is dynamically adjusted by learning the task uncertainty parameter $s_k$. The hyperparameter $\alpha$ is used to control the strength of the GradNorm loss, while $\lambda$ serves as the regularization coefficient.

## 4. Experiments

### 4.1. Datasets and Metrics

**CUHK-PEDES** [20] is the first benchmark for text-to-image person re-identification, comprising 40,206 images of 13,003 identities with two textual descriptions per image. Following the official protocol, we partition the dataset into training (11,003 identities), validation (1,000 identities), and testing (1,000 identities) sets.

**ICFG-PEDES** [46] consists of 54,552 images across 4,102 identities, each annotated with a single human-written description. The official split allocates 3,102 identities for training and 1,000 for testing.

**RSTPReid** [7] captures 20,505 images of 4,104 identities from 15 cameras, with five viewpoint-diverse images and two descriptions per identity. We adopt the standard split: 3,701 identities for training and 200 each for validation and testing.

**Evaluation Metrics.** We report Rank-k accuracy (R-1, R-5, R-10) and mean Average Precision (mAP), consistent with prior works in this domain.

### 4.2. Implementation Details

Our model employs the 'bert-base-uncased' model, which is pre-trained, as the text encoder with a hidden dimensionality of 768. We use 'vit-base-patch16-224' as the visual encoder. All images are resized to $224 \times 224$ pixels. The BDAM module processes visual tokens through multiple layers of self-attention and cross-attention, disentangling them into identity and clothing features of 768 dimensions each. A Mamba fusion module with two layers, configured with an input and output dimension of 256, a state dimension of 16, and a convolutional kernel size of 4, integrates the multimodal representations. The dropout rate is set to 0.1 throughout.

Training utilizes the Adam optimizer with a learning rate of $1 \times 10^{-4}$, weight decay of $1 \times 10^{-3}$, and cosine annealing scheduling. The loss function for multiple tasks combines InfoNCE, triplet, clothing adversarial, HSIC decoupling, and gate regularization terms. We employ GradNorm

for dynamic task weighting with $\alpha = 1.5$ and a weight learning rate of 0.025. Task weights are normalized to sum to the number of tasks and clipped to the range $[10^{-4}, 10]$. Gradient norms are computed on the final shared layer, with an additional regularization coefficient for log variance of $1 \times 10^{-3}$.

For data augmentation, we extract style embeddings using 'clip-vit-base-patch32', cluster them via DBSCAN, and generate descriptions consistent with the style for identity and clothing through 'ChatGPT-4'. All splits are enforced at the identity level to prevent data leakage. Each experiment is repeated with random seeds 0, 1, and 2; we select the best checkpoint based on validation performance and report the mean across the three runs.

### 4.3. Parameter Analysis

Although the identity and clothing branches in BDAM adopt identical architectures, they learn distinctly different representations through independent parameterization and asymmetric supervision. The BDAM gating mechanism generates weights at the dimension level $g_{\text{dis}} \in \mathbb{R}^{B \times D}$ via $g_{\text{dis}} = \sigma(W_g[\hat{f}_{id}; \hat{f}_{clo}] + b_g)$. This yields complementary coefficients $W_{id} = g_{\text{dis}}$ and $W_{clo} = 1 - g_{\text{dis}}$ that satisfy the constraint $W_{id} + W_{clo} = 1$. This constraint introduces competitive pressure between branches, encouraging each to specialize in unique semantic patterns.

The learning dynamics are governed by asymmetric loss signals. The identity branch receives supervision from InfoNCE and triplet losses, steering it toward attributes that are invariant to the person, such as body shape and posture. In contrast, the clothing branch is guided by matching and adversarial losses toward features centered on appearance. The decoupling loss based on HSIC enforces statistical independence by orthogonalizing the two feature subspaces in a Reproducing Kernel Hilbert Space, thereby preventing representational collapse.

Similarly, the fusion module employs an adaptive gating mechanism to balance modality contributions. The fusion gate $g_{\text{fus}} \in \mathbb{R}^{B \times 2}$ is computed as $g_{\text{fus}} = \text{Softmax}(W_f[f_{\text{img}}; f_{\text{txt}}])$, producing normalized modality weights $W_{\text{img}} = g_{\text{fus}}[:, 0]$ and $W_{\text{txt}} = g_{\text{fus}}[:, 1]$ satisfying $W_{\text{img}} + W_{\text{txt}} = 1$. This mechanism operates at the instance level, dynamically adjusting modality importance based on input characteristics, whereas the disentanglement gate provides control at the dimension level within the visual stream. To empirically validate these mechanisms, we analyze the distributions of learned gate weights across the test set, as shown in Fig. 3. The BDAM identity weights exhibit a distribution skewed to the right, with a mean of 0.61 and standard deviation of 0.17, substantially exceeding the clothing weights which concentrate around 0.38. This asymmetry
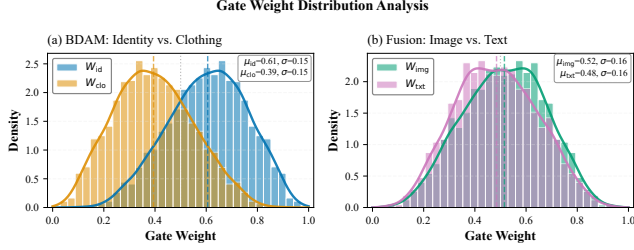
Figure 3. Learned gate weight distributions on the CUHK-PEDES test set. (a) BDAM assigns significantly higher weights to identity features than clothing features, validating the identity-centric design. (b) Fusion module maintains balanced modality contributions, confirming effective cross-modal integration without modality dominance.

confirms that features relevant to identity dominate the final representation, aligning with our design centered on identity. The bimodal separation pattern indicates the gate has learned to discriminate between samples with strong identity cues versus those requiring additional contextual information. In contrast, the fusion module maintains nearly equal modality contributions, with means of 0.52 for image and 0.48 for text, both with moderate variance around 0.10. This balanced distribution, centered near the uniform baseline of 0.5, demonstrates stable alignment between modalities without collapse toward either one.

These empirical observations corroborate our theoretical design: BDAM enforces semantic disentanglement through asymmetric supervision and regularization via HSIC, while the fusion gate achieves dynamic equilibrium via Softmax normalization and balanced loss weighting.

### 4.4. Ablation Study

We conduct systematic ablation studies to validate the contribution of each architectural component and loss term. All experiments are performed on CUHK-PEDES unless otherwise specified.

Table 1. Ablation study on the BDAM module.

| Method | mAP(%) ↑ | R-1(%) ↑ | R-5(%) ↑ | R-10(%) ↑ |
|---|---|---|---|---|
| Baseline(w/o BDAM) | 59.81 | 70.54 | 85.49 | 91.26 |
| + BDAM | 66.74 | 76.27 | 89.30 | 94.02 |
| w/o Cross-Attn | 62.56 | 71.39 | 87.05 | 92.98 |
| w/o Gate | 65.11 | 74.63 | 88.77 | 93.56 |
| Shallow(3-layer) | 64.27 | 73.74 | 88.09 | 93.32 |

**Disentanglement Module.** As shown in Tab. 1, incorporating BDAM yields substantial improvements over the baseline, demonstrating the effectiveness of explicit disentanglement between identity and clothing. The subsequent analysis of its components confirms the necessity of each design choice. Removing the bidirectional cross attention, ablat-

ing the gating mechanism, or reducing the network depth to three layers all result in significant performance degradation. This indicates that the semantic interaction between branches, the adaptive feature control, and sufficient model depth are all essential for achieving robust disentanglement. The learned gate weight distributions in Fig. 3 provide additional evidence, showing that the gating mechanism automatically achieves semantic specialization in BDAM and modality balance in fusion through end to end training.
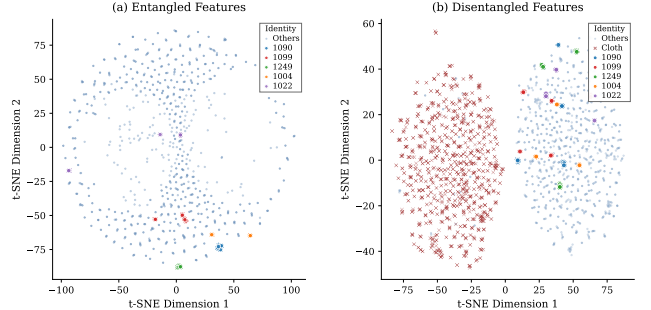


Figure 4. Visualization of feature distributions using t-SNE. (a) The baseline model exhibits highly entangled features with poor identity separation. (b) Our method (BDAM with HSIC) yields a highly organized space, clearly decoupling identity (dots) from clothing (crosses) features.

To provide a qualitative assessment of disentanglement quality, we visualize the learned feature space using dimensionality reduction via t-SNE in Fig. 4. The visualization reveals a stark contrast. The baseline model (a) produces a highly mixed embedding space where identities overlap, indicating severe entanglement between identity and appearance attributes. (b) Conversely, our method, incorporating BDAM with HSIC regularization, yields a highly organized feature space. The identity embeddings form tight clusters, exhibiting strong cohesion for samples of the same person and clear separation between different identities. Concurrently, clothing features are projected to an independent region. This geometric structure confirms the orthogonality enforced by our disentanglement mechanism and provides visual evidence for the quantitative performance gains observed in Tab. 1.

Table 2. Ablation study on the fusion module.

| Method | mAP(%) ↑ | R-1(%) ↑ | R-5(%) ↑ | R-10(%) ↑ |
|---|---|---|---|---|
| Baseline(w/o Fusion) | 59.81 | 70.54 | 85.49 | 91.26 |
| Full Fusion | 69.58 | 78.42 | 90.74 | 95.11 |
| w/o Mamba | 66.89 | 75.73 | 89.06 | 93.92 |
| w/o Gate | 68.64 | 77.58 | 90.11 | 94.87 |
| w/o Alignment | 68.15 | 77.09 | 89.84 | 94.53 |

**Fusion Module.** The analysis in Tab. 2 confirms that the effectiveness of our complete fusion module, which substan-

tially outperforms the baseline, stems from the synergy of its three components. The Mamba SSM backbone is identified as the most critical element; its removal incurs the largest performance drop, highlighting the importance of modeling dependencies over long ranges across modalities. Furthermore, the gating mechanism and modality alignment layers provide essential complementary benefits. Ablating either component results in a clear degradation, confirming their respective roles in enabling adaptive weighting and achieving distributional alignment.

Table 3. Ablation study on individual loss components.

| Method | mAP(%) ↑ | R-1(%) ↑ | R-5(%) ↑ | R-10(%) ↑ |
|---|---|---|---|---|
| Full Model | 72.61 | 79.93 | 92.95 | 96.47 |
| w/o InfoNCE | 28.14 | 36.55 | 55.21 | 65.83 |
| w/o Triplet | 67.22 | 74.89 | 88.15 | 93.12 |
| w/o Adversarial | 69.15 | 76.92 | 89.53 | 94.22 |
| w/o Decoupling | 70.03 | 77.81 | 90.11 | 94.98 |
| w/o Gate Reg. | 71.98 | 79.23 | 91.35 | 95.71 |

**Loss Functions.** To validate the necessity of each loss component, we systematically remove individual terms while keeping all other settings fixed. As shown in Tab. 3, every loss term contributes positively to the final performance. The InfoNCE and triplet losses emerge as foundational. Removing InfoNCE causes a catastrophic performance collapse, underscoring the critical importance of contrastive alignment between modalities. Ablating the triplet loss also significantly degrades retrieval accuracy, confirming the necessity of strong identity discrimination within a modality. The losses specific to disentanglement, namely the adversarial and HSIC decoupling losses, are likewise essential. The performance degradation upon removing either term demonstrates that architectural design alone is insufficient; explicit constraints imposed by the loss function are required to enforce the separation of identity and clothing. Finally, the minor but consistent degradation from removing gate regularization validates its auxiliary role in stabilizing the learned gating mechanisms.

Table 4. Ablation study on clustering strategies for style prompt generation.

| Method | mAP(%) ↑ | R-1(%) ↑ | R-5(%) ↑ | R-10(%) ↑ |
|---|---|---|---|---|
| Baseline (w/o Style) | 71.22 | 79.18 | 91.51 | 95.79 |
| + Random | 71.95 | 79.54 | 91.66 | 95.82 |
| + K-Means | 71.85 | 79.20 | 91.60 | 95.90 |
| + GMM | 71.70 | 79.05 | 91.50 | 95.75 |
| + Agglomerative | 71.78 | 79.10 | 91.55 | 95.80 |
| + HDBSCAN | 72.20 | 79.40 | 91.95 | 96.10 |
| + DBSCAN (Ours) | 72.61 | 79.93 | 92.95 | 96.47 |

**Style Prompt Generation.** We compare various clustering algorithms for generating prompts consistent with style, as detailed in Tab. 4. While random sampling provides minimal gains over the baseline, demonstrating the importance of a structured prompt design, traditional methods such as K-Means, Gaussian Mixture Models, and Hierarchical Agglomerative clustering offer only modest improvements. These methods are constrained by limitations such as the manual specification of cluster counts and difficulty handling irregular density distributions. In contrast, approaches based on density, particularly DBSCAN, achieve superior performance. This is because DBSCAN automatically discovers clusters of arbitrary shape while identifying and filtering noise. DBSCAN's ability to adaptively determine the number of style categories without requiring hyperparameter tuning makes it the optimal choice for this task.
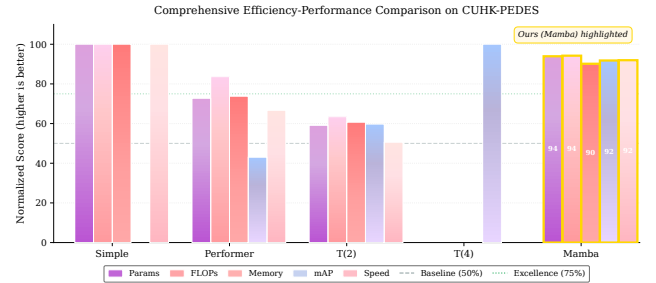
### 4.5. Efficiency Analysis



Figure 5. Comparison of efficiency and performance on CUHK-PEDES. All metrics are normalized to [0, 100], where higher is better. Cost metrics (Params, FLOPs, Memory) are inverted, meaning lower resource usage yields a higher score. Our fusion module employing Mamba achieves competitive accuracy with reduced computational overhead.

As shown in Fig. 5, our fusion module employing Mamba achieves an optimal balance in the trade-off between accuracy and efficiency. The visualization reveals that Mamba maintains performance near the peak across all dimensions. Compared to the four-layer Transformer baseline, our method delivers competitive retrieval accuracy (reflected in comparable mAP scores) while achieving substantially higher efficiency scores in Params, FLOPs, and Memory, which confirms lower computational overhead. Against the Simple baseline, Mamba demonstrates marked mAP improvements while maintaining comparable efficiency scores, validating superior resource utilization.

### 4.6. Comparisons with State-of-the-Art Methods

We compare our method against recent state-of-the-art approaches across three benchmarks, as summarized in Tab. 5. On CUHK-PEDES, our method establishes new state-of-the-art results, substantially surpassing both ViT-based meth-

Table 5. Performance comparison with state-of-the-art methods on three benchmark datasets.

| Method | Backbone | CUHK-PEDES | | | | ICFG-PEDES | | | | RSTPReid | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | R-1 | R-5 | R-10 | mAP | R-1 | R-5 | R-10 | mAP | R-1 | R-5 | R-10 | mAP |
| *Methods with CLIP backbone:* | | | | | | | | | | | | | |
| IRRA [15] | CLIP-ViT | 73.38 | 89.93 | 93.71 | 66.10 | 63.36 | 80.82 | 85.82 | 38.06 | 60.20 | 81.30 | 88.20 | 47.17 |
| IRLT [24] | CLIP-ViT | 73.67 | 89.71 | 93.57 | 65.94 | 63.57 | 80.57 | 86.32 | 38.34 | 60.51 | 82.85 | 89.71 | 47.64 |
| CFAM [48] | CLIP-ViT | 74.46 | 90.19 | 94.01 | - | 64.72 | 81.35 | 86.31 | - | 61.49 | 82.26 | 89.23 | - |
| Propot [41] | CLIP-ViT | 74.89 | 89.90 | 94.17 | 67.12 | 65.12 | 81.57 | 86.97 | 42.93 | 61.87 | 83.63 | 89.70 | 47.82 |
| RDE [27] | CLIP-ViT | 75.94 | 90.14 | 94.12 | 67.56 | 67.68 | 82.47 | 87.36 | 40.06 | 65.35 | 83.95 | 89.90 | 50.88 |
| HAM [16] | CLIP-ViT | 77.99 | 91.34 | 95.03 | 69.72 | 69.95 | 83.88 | 88.39 | 42.72 | 72.50 | 87.70 | 91.95 | 55.47 |
| *Methods with ViT backbone:* | | | | | | | | | | | | | |
| CPCL [45] | ViT | 70.03 | 87.28 | 91.78 | 63.19 | 62.60 | 79.07 | 84.46 | 36.16 | 58.35 | 81.05 | 87.65 | 45.81 |
| PDReid [21] | ViT | 71.59 | 87.95 | 92.45 | 65.03 | 60.93 | 77.96 | 84.11 | 36.44 | 56.65 | 77.40 | 84.70 | 45.27 |
| SSAN [7] | ViT | 61.37 | 80.15 | 86.73 | - | 54.23 | 72.63 | 79.53 | - | 43.50 | 67.80 | 77.15 | - |
| CFine [39] | ViT | 69.57 | 85.93 | 91.15 | - | 60.83 | 76.55 | 82.42 | - | 50.55 | 72.50 | 81.60 | - |
| IVT [32] | ViT | 65.59 | 83.11 | 89.21 | - | 56.04 | 73.60 | 80.22 | - | 46.70 | 70.00 | 78.80 | - |
| **Ours** | ViT | **79.93** | **92.95** | **96.47** | **72.61** | **68.68** | **84.29** | **89.74** | **41.78** | **74.33** | **88.85** | **92.95** | **57.68** |

ods and the recent CLIP-based HAM baseline. On ICFG-PEDES, our approach remains competitive with HAM while significantly outperforming other methods. On RSTPReid, we achieve the best reported results to date, surpassing all ViT-based methods and establishing clear improvements over HAM.

These consistent gains across diverse datasets underscore the generalization capability of our approach. Notably, this high performance is achieved without leveraging large-scale pre-trained vision-language models, demonstrating that our identity-clothing disentanglement architecture and efficient fusion strategy provide effective cross-modal alignment through task-specific design. In summary, our method delivers superior or highly competitive performance across all three benchmarks, validating the effectiveness of our proposed components for text-to-image person re-identification.

## 5. Conclusion and Limitations

In this work, we proposed a novel framework to address interference caused by clothing in text-to-image person re-identification. Our approach is centered on feature decoupling guided by a Multimodal Large Language Model. We successfully demonstrated that an MLLM can provide supervision at a fine-grained level to guide our Bidirectional Decoupling Alignment Module. By design, this module explicitly isolates features relevant to identity while actively suppressing interference related to clothing through a combined adversarial and orthogonal loss strategy based on a kernel function. Furthermore, our integration of a Mamba State Space Model proved to be an effective and efficient fusion strategy, adept at capturing dependencies between modalities. Our method's effectiveness was validated by

achieving new state-of-the-art results on the CUHK-PEDES and RSTPReid benchmarks.

Nonetheless, limitations remain. These primarily concern the potential for noise in descriptions generated by the MLLM and the need for further optimization for deployment at a large scale. Future work will focus on improving description reliability to mitigate noise and on enhancing inference efficiency. We also plan to explore the framework's applicability to more challenging scenarios, such as person Re-ID involving clothing changes, to further test the robustness of our decoupling mechanism.

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