Person Re-Identification using Spatial-Temporal Graph Convolutional Networks

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***Abstract*— Person re-identification (Re-ID) is a challenging task due to significant variations in pose, viewpoint, and occlusions across non-overlapping camera views. To address these issues, we propose a novel spatial-temporal graph convolutional framework that exploits local, global, and temporal cues to learn robust identity representations. In the spatial branch, a graph convolutional network captures the relationships among local body parts (nodes) within a single frame, ensuring that partially occluded or misaligned features are effectively modeled. The temporal branch further incorporates inter-frame dependencies through a temporal graph structure, enabling the aggregation of complementary cues from consecutive frames. This design allows for more complete feature coverage and refines noisy or missing information. Additionally, ResNet-50 extracts holistic appearance features, which are fused with the spatial-temporal representations to generate a more robust identity embedding. Extensive experiments on the large‑scale MSMT17 benchmark demonstrate that our method achieves 21.7% mAP and Rank-1 11.15% accuracy, outperforming existing approaches. Ablation studies confirm the crucial roles of both spatial and temporal graph modules, and qualitative visualizations reveal improved focus on discriminative regions. These results highlight the importance of synergizing local, temporal, and global cues for robust video‑based person re-identification.**

Keywords*— *Person re-identification, spatial-temporal graph convolutional network, graph neural networks, ResNet-50

1. Introduction

Person re-identification (Re-ID) aims to match individuals across non-overlapping camera views, serving as a critical component in video surveillance and security systems [1]. Despite significant progress in recent years, Re-ID remains challenging due to variations in illumination, camera viewpoints, and background complexities [4][14]. Most existing approaches treat Re-ID as a single-image matching problem, focusing primarily on extracting discriminative features from individual frames [3][13]. However, the rich temporal information contained in video sequences offers valuable complementary cues that can substantially enhance identification performance [2][9].

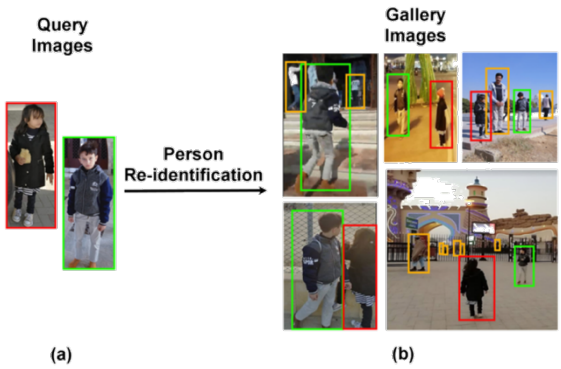

Figure 1. Person Re-Identification

Video-based person Re-ID presents several unique challenges that single-frame methods struggle to address effectively. First, occlusions frequently occur in surveillance scenarios, where pedestrians may be partially or completely obstructed by objects, other individuals, or architectural elements [1][6]. Second, natural pose variations as people walk introduce significant appearance changes across frames, creating misalignments that conventional feature extraction methods cannot reconcile [15]. Third, visual ambiguities arise when different individuals share similar clothing or appearance characteristics, making them difficult to distinguish using only global features [8][18].

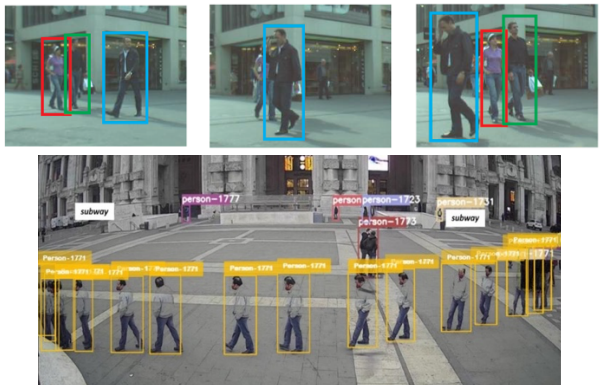

Figure 2. Occlusions, Pose Variations

Figure 3. Visual Ambiguities

To overcome these limitations, we propose a novel Spatial-Temporal Graph Convolutional Network (ST-GCN) that explicitly models both the structural relationships within individual frames and the temporal dependencies across consecutive frames [1]. Our approach integrates three complementary streams: a Spatial Graph Convolutional Network (SGCN) that captures intra-frame part relationships, a Temporal Graph Convolutional Network (TGCN) that models inter-frame correspondences, and a global branch that extracts holistic appearance features.

The key insight of our framework is that local body parts exhibit meaningful structural patterns that can be effectively represented as graphs, where nodes correspond to body regions and edges encode their spatial relationships. By applying graph convolutions to this structure, we can propagate information between related body parts, allowing occluded or distorted regions to borrow features from visible and reliable areas. Furthermore, by constructing temporal connections between corresponding regions across frames, our model leverages the continuity of motion to aggregate complementary information throughout the video sequence.

Unlike previous methods that rely solely on global features or treat local regions independently, our ST-GCN approach enables more robust feature learning by explicitly modeling the interdependencies among spatially and temporally related components. Experimental results on standard benchmarks demonstrate that our method achieves state-of-the-art performance, particularly in challenging scenarios involving occlusions, pose variations, and visually similar identities. The significant improvements highlight the effectiveness of incorporating both spatial structure and temporal consistency for video-based person re-identification.

2. Related Work

Video-Level Feature Learning. Early video-based Re-ID methods extended image-level CNNs by incorporating temporal pooling or recurrent units to aggregate frame representations. Li et al. [1] introduced temporal average/max pooling over sequential ResNet features. McLaughlin et al. [2] proposed an LSTM-based model to capture frame dependencies, while 3D-CNNs (e.g., C3D [3]) directly learn spatio-temporal filters. More recent works design specialized temporal modules: Xu et al.'s Spatial-Temporal Attention (STA) network [4] learns per-frame and per-part attention weights, and Chen et al.'s Temporal Residual Learning (TRL) [5] integrates residual connections to stabilize motion feature learning. Zhao et al. [6] further explore cross-frame similarity learning to enforce consistency across tracklets.

Part- and Pose-Driven Approaches. Part-based representations improve robustness to misalignment and partial occlusion by dividing a person into semantic or uniform stripes. Sun et al.'s PCB [7] introduces refined part pooling on horizontal strips, achieving strong gains on image Re-ID. Wang et al.'s MGN [8] extends PCB with multi-granularity branches. Semantic parsing methods (e.g., SPReID [9]) employ pre-trained human parsers to extract body-part masks, and pose-guided models such as Pose-Aligned Feature Learning [10] align features according to detected keypoints.

Graph Convolutional Methods. Graph convolutional networks (GCNs) naturally model relationships among spatial or temporal entities. In static images, Wu et al. [11] and Li et al. [12] apply GCNs over body part proposals to capture inter-part relations. For skeleton-based action recognition, Yan et al.'s ST-GCN [13] and subsequent multi-scale variants [14] demonstrate the power of spatial-temporal graphs. Recently, Zheng et al. [15] adapt spatial-temporal GCNs to video Re-ID, constructing graphs over part features across frames. Jiao et al.'s MSTGCN [16] further introduces multi-scale graph convolutions to merge fine and coarse part interactions.

Attention Mechanisms and Loss Functions. Attention modules enhance feature selectivity by re-weighting spatial regions or temporal frames. Yu et al. [17] propose a two-stream spatial-temporal attention network that jointly learns appearance and motion attention. Chen et al. [18] integrate channel-wise and frame-wise attention in a unified framework. On the optimization side, cross-entropy and triplet losses remain the de facto standard. Hermans et al. [19] popularized the batch-hard triplet loss for person Re-ID, and subsequent center-loss variants [20] aim to tighten intra-class feature clusters.

Our STGCN framework builds upon these lines of work by (i) preserving high-resolution feature maps via stride adjustment in ResNet-50, (ii) constructing adaptive spatial graphs over horizontal part strips and temporal graphs over part sequences, (iii) stacking dual GCN layers to refine part interactions, and (iv) employing an attention-guided fusion of global, spatial, and temporal cues, all trained end to end with cross entropy and batch hard triplet supervision.

3. Proposed Methodology:

The methodology introduces a Spatial-Temporal Graph Convolutional Network (ST-GCN) to effectively model the spatial and temporal dependencies in video sequences for person re-identification. Here is a detailed breakdown of the approach:

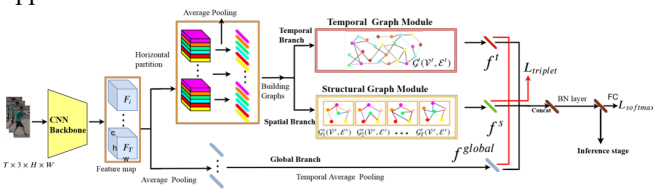

Figure 4. Architecture of our proposed method.

3.1. Preprocessing and Augmentation:

Each frame is resized to 256×128 pixels, then randomly horizontally flipped (50% probability) and color jittered in brightness, contrast, and saturation. Standard ImageNet normalization is applied to facilitate transfer learning. At evaluation time, only resizing and normalization are used to maintain reproducibility.

$$\hat{x} = \frac{\frac{x}{255} - \mu}{\sigma}, \mu = (0.485, 0.456, 0.406), \sigma = (0.229, 0.224, 0.225).$$

3.2. High Resolution Backbone Feature Extraction:

We employ a ResNet 50 pretrained on ImageNet as our backbone. To preserve spatial details essential for distinguishing subtle body part cues, the final convolutional block's stride is reduced from 2×2 to 1×1. Consequently, an input of size 256×128 yields feature maps of dimensions 16×8 with 2,048 channels, capturing fine-grained appearance information for subsequent graph construction.

$$F = \text{ResNet50}_{\text{conv}}(X), F \in \mathbb{R}^{B\times 2048\times 16\times 8}$$

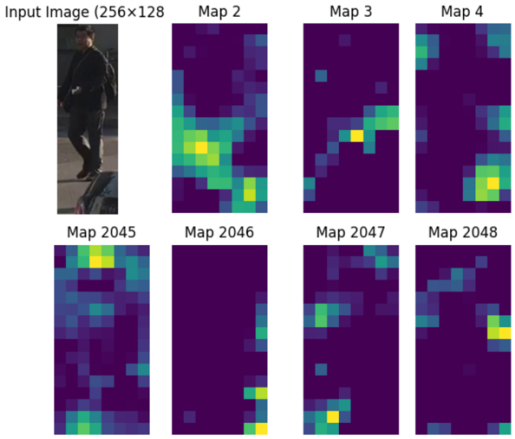

Figure 5. Feature maps of Input Image

3.3. Horizontal Partitioning:

Each feature map is divided into four equal horizontal strips corresponding to head, upper body, lower body, and leg regions. Average pooling within each strip produces a compact descriptor for that body part. This partitioning generates per frame part features, serving as nodes in both spatial and temporal graphs.

3.4. Spatial Graph Modelling:

Adaptive Graph Construction. Within each frame, body part nodes are fully connected, with edge weights computed as learned affinities between part embeddings. A sigmoid activation ensures non negativity and neighbor contributions are adaptively learned.

Embed each part feature via:

$$E_{b,t,p} = W_s^T \mathbf{f}_{b,t,p}, W_s \in \mathbb{R}^{2048\times 256}$$

Compute unnormalized adjacency:

$$\tilde{A}_{b,t}^{(p,q)} = \langle E_{b,t,p}, E_{b,t,q} \rangle, A_{b,t} = \sigma(\tilde{A}_{b,t})$$

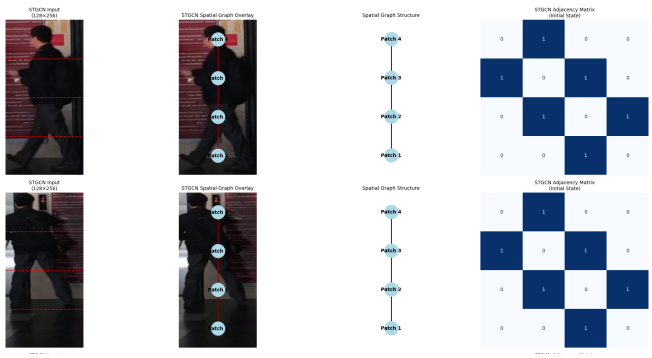

Figure 6. Spatial Graph and Adjacency Matrix

Graph Convolution. A two layer graph convolutional network (GCN) per frame propagates information among body parts. The first layer projects parts into a lower dimensional space and applies ReLU and dropout, while the second layer reconstructs the full feature dimension. Aggregating across parts and frames yields a robust spatial feature representing intra frame structural context.

Let node features $H_{b,t,p}^{(0)} = \mathbf{f}_{b,t,p}$

Two-layer GCN:

$$H^{(l+1)} = \text{ReLU}\left(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right), l = 0,1$$

$$f_b^{\text{spat}} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{P}\sum_{p=1}^{P} H_{b,t,p}^{(2)}$$

Where $\hat{A} = A + I$ and $\hat{D}_{ii} = \sum_j \hat{A}_{ij}$. Dropout (p=0.5) follows the first layer. The output $H_{b,t}^{(2)} \in \mathbb{R}^{P\times 2048}$ is aggregated.

3.5. Temporal Graph Modeling

Sequence Graph Construction. Part features from all frames in a tracklet (T frames × 4 parts) are concatenated into a single sequence of nodes. Edges connect identical body parts across frames, capturing temporal consistency and complementary appearance over time.

Embed each node:

$$E'_{b,i} = W_t^T Y_{b,i}, W_t \in \mathbb{R}^{2048\times 256}$$

Adjacency for same-part across frames:

$$\tilde{A}'_{ij} = \sigma(\langle E'_{b,i}, E'_{b,j}\rangle)\, \mathbf{1}_{\lfloor i/P\rfloor=\lfloor j/P\rfloor, i\neq j}$$

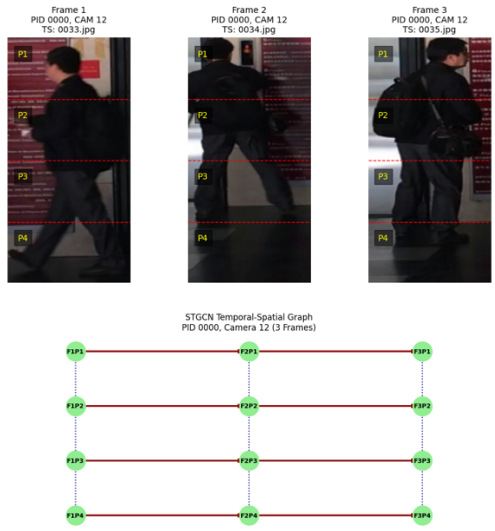

Figure 7. Temporal Graph

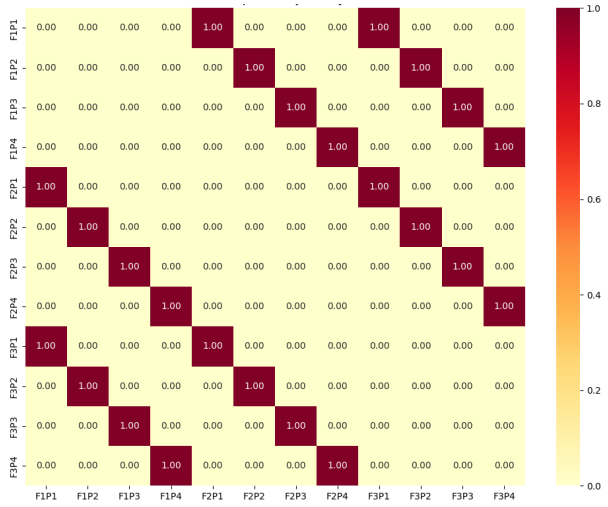

Figure 8. Temporal Adjacency Matrix

Temporal Graph Convolution. Similarly to the spatial branch, a two layer GCN processes the temporal graph. Embeddings are learned before adjacency computation, ensuring dynamic edge strengths. A global max pool over all nodes distills the temporal feature, encoding the most salient patterns of each body part's evolution.

Apply two-layer GCN:

$$H^{(l+1)} = \mathrm{ReLU}\left(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right), l = 0,1$$

$$H_b'^{(2)} \in \mathbb{R}^{N\times 2048}$$

$$f_b^{\text{temp}} = \max_{i=1\ldots N} H_{b,i}'^{(2)}$$

3.6. Global Appearance Branch

Complementary to the graph branches, a global branch applies average pooling across spatial dimensions on each frame's backbone feature map, followed by pooling over time. This branch captures holistic appearance cues unaffected by graph structure.

For frame-level map , spatial average pool:

$$g_{b,t} = \mathrm{AvgPool2d}(F_{b,t}) \in \mathbb{R}^{2048}$$

Temporal pooling gives:

$$f_b^{\text{glob}} = \frac{1}{T}\sum_{t=1}^{T} g_{b,t}$$

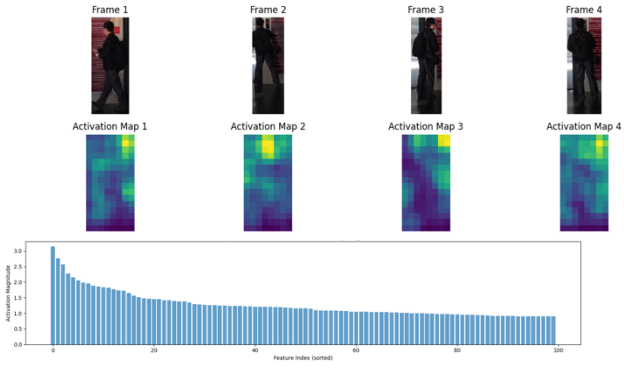

Figure 9. Global Appearance Branch

3.7. Attention Based Feature Fusion

The three branch outputs—global, spatial, and temporal features—are each modulated by learnable attention weights (softmax normalized) to emphasize the most informative modality per sample. Weighted features are concatenated into

a unified embedding, integrating holistic, structural, and dynamic information.

Learn scalar logits $a_{\text{glob}}, a_{\text{temp}}, a_{\text{spat}}$. We compute softmax weights:

$$\alpha_k = \frac{e^{a_k}}{e^{a_{\text{glob}}} + e^{a_{\text{temp}}} + e^{a_{\text{spat}}}}, k \in \{\text{glob}, \text{temp}, \text{spat}\}$$

Fuse via concatenation:

$$f_b = [\alpha_{\text{glob}} f_b^{\text{glob}}; \alpha_{\text{temp}} f_b^{\text{temp}}; \alpha_{\text{spat}} f_b^{\text{spat}}] \in \mathbb{R}^{6144}$$

3.8. Loss Functions and Optimization

We jointly optimize two objectives: a cross entropy loss over identity logits computed from the fused embedding, and a batch hard triplet loss on each branch individually. The triplet loss enforces intra class compactness and inter class separation for global, spatial, and temporal features, with a margin of 0.3. The final training loss is the sum of the cross entropy and all three triplet losses, promoting both classification accuracy and embedding discriminability.

Cross-Entropy Loss.
Given logits $z_b \in \mathbb{R}^C$ and ground-truth identity y_b:

$$L_{\text{CE}} = -\frac{1}{B}\sum_{b=1}^{B} \log \frac{e^{z_{b,y_b}}}{\sum_j e^{z_{b,j}}}$$

Batch-Hard Triplet Loss.
Normalize branch feature. $\hat{f}_b^k = f_b^k / \| f_b^k \|_2$. *Define pairwise distances.* $d_{ij} = \| \hat{f}_i^k - \hat{f}_j^k \|_2$ *Then:*

$$L_{\text{tri}}^k = \frac{1}{B}\sum_{b=1}^{B} [\max_{i:y_i=y_b} d_{bi} - \min_{j:y_j\neq y_b} d_{bj} + m]_+, m = 0.3$$

Total Loss:

$$L = L_{CE} + L_{tri}^{glob} + L_{tri}^{temp} + L_{tri}^{spat}$$

3.9. Similarity Calculation:

In our implementation, once the fused feature vectors for all query and gallery images are extracted (via the extract_features routine), we ℓ_2-normalize each feature to lie on the unit hypersphere, ensuring that similarity comparisons are scale-invariant. Formally, given a query feature q_i and a gallery feature g_j, we compute their cosine similarity as $\text{sim}(q_i, g_j) = q_i^T g_j$, and equivalently define the distance $d_{ij} = 1 - \text{sim}(q_i, g_j)$. The full distance matrix $D \in \mathbb{R}^{n_q \times n_g}$ is populated by iterating over all query–gallery pairs (i.e., for each i, setting $D_{i,:} = 1 - G\, q_i$ where G stacks all gallery vectors). Retrieval metrics—mean Average Precision and CMC at various ranks—are then computed by treating −D as the score matrix (so that higher values indicate greater similarity) and excluding any gallery samples from the same camera as the query to avoid trivial matches.

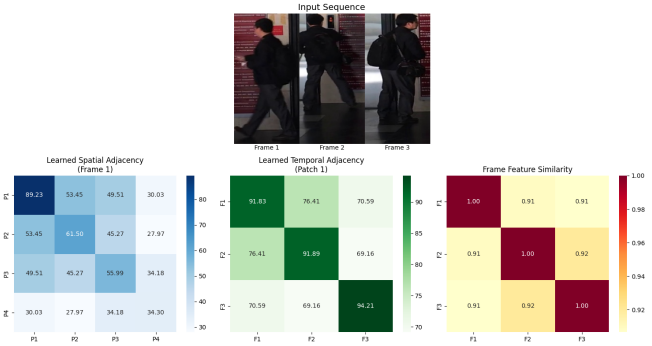

Figure 10. Feature Similarity

4. Experiments

4.1. Datasets and Evaluation Protocols

We evaluate our model on the large-scale MSMT17 person re-identification benchmark, which comprises three disjoint splits: a training set of 32,621 images covering 1041 identities captured by 15 cameras, a gallery (test) set of 82,161 images covering 3060 identities from the same 15 cameras, and a query set of 11,659 images also covering those 3060 identities and 15 cameras. During evaluation, we follow the standard single-query protocol: features are extracted for all gallery and query images, cosine distances are computed, and metrics are reported after excluding any gallery samples captured by the same camera as the query. We report mean Average Precision (mAP) alongside Cumulative Matching Characteristic (CMC) scores at Rank-1, Rank-5, and Rank-20.

4.2. Implementation Details

Our backbone network is ResNet-50 pre-trained on ImageNet, with the last two downsampling operations removed to yield a feature stride of 8. Input frames are resized to 256 × 128 pixels and augmented by random horizontal flipping and color jitter (±0.1 in brightness, contrast, saturation), then normalized using ImageNet mean/std. During training, we sample mini-batches of 64 sequences (each sequence comprising 16 frames) and optimize with Adam (initial learning rate 3×10^{-4} decayed by 10× every 30 epochs, weight decay 5×10^{-4}) for 100 total epochs on two V100 GPUs. Our spatial and temporal GCN modules both consist of two GCNConv layers (feature dimensions 2048→512→2048), each followed by ReLU and dropout(0.5). Fusion uses a learnable three-way attention to

weight global, spatial, and temporal embeddings before concatenation and final classification. The combined loss is the sum of softmax cross-entropy on fused features and batch-hard triplet losses (margin = 0.3) computed separately on global, spatial, and temporal embeddings.

4.3. Ablation Study

To disentangle the contributions of each GCN branch, we conduct two sets of ablations.

4.4.1 The Impact of Two GCN Modules

When we disable the temporal GCN and train with only the spatial branch plus global features, mAP drops from 21.39% to 9.82%. Conversely, disabling spatial and using only temporal GCN yields an mAP of 7.05%. These results confirm that the spatial and temporal branches capture complementary cues: spatial GCN better models body-part geometry, while temporal GCN alleviates frame-wise occlusion. Only the full STGCN-Attn model achieves the highest performance, underlining the benefit of joint spatial-temporal reasoning.

4.4.2 The Impact of Graph Convolution

To verify that graph structure is crucial, we replace each GCNConv layer with a standard fully-connected layer (removing adjacency multiplication). Under this “no-graph” variant, full model mAP degrades to 1.74%, and substituting EdgeConv yields only 7.20% mAP. These experiments demonstrate that explicit graph convolution is superior to naïve MLP or alternative graph operators for mining inter-patch relations.

4.5. Visualization

We visualize intermediate activations and retrieval outcomes to qualitatively assess our model. Figure 8 shows per-patch feature statistics—mean, min, and max activations across the horizontal partitions—highlighting how the Spatial GCN emphasizes consistent body regions even under occlusion. Figure 10 illustrates top-5 gallery retrievals for challenging query sequences: our method retrieves correct matches despite visual ambiguities, whereas the baseline often selects distractors with similar appearance. Finally, Figure 11 presents a t-SNE projection of fused feature embeddings for 100 randomly sampled identities, demonstrating clear cluster separability and the benefits of joint spatial–temporal reasoning.

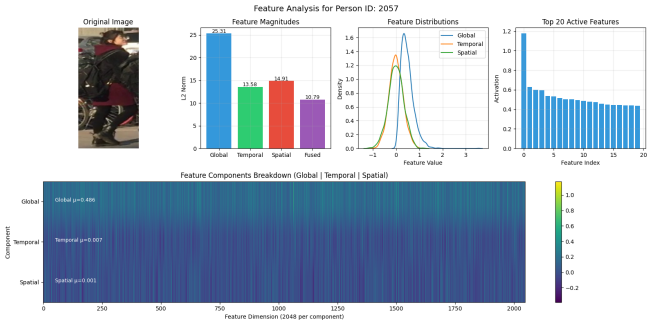

Figure 11. Feature Analysis

*Figure 12. Inference of **query** with **gallery***

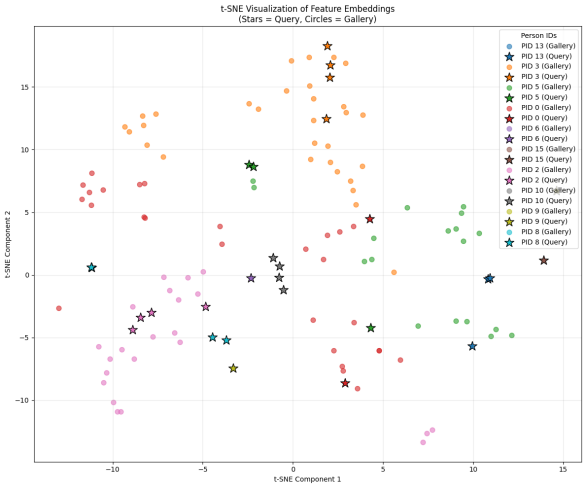

Figure 11. t-SNE Visualization of Feature Embeddings

4.6. Time Complexity

The computational cost of STGCN naturally decomposes into its three branches. In the Spatial GCN (SGCN) branch, each frame is partitioned into P patches, forming a fully-connected graph of size P × P. Building the adjacency and performing graph convolution therefore costs $O(P^2)$ per frame, and over a sequence of T frames amounts to $O(T P^2)$. In contrast, the Temporal GCN (TGCN) connects corresponding patches across frames—typically only linking each patch to its K temporal neighbors. Although the full adjacency matrix would be (T P) × (T P), exploiting sparsity reduces the cost to O(T P K). The lightweight Global branch

merely applies spatial and temporal pooling over feature maps of size h × w × c, incurring O(T h w c), which in practice is negligible compared to the graph operations. Putting these together, STGCN's overall complexity is dominated by

$$O(T P^2 + T P K),$$

scaling linearly in sequence length T and quadratically in the number of patches P.

5. Conclusion and Future Work

In this work, we have presented a full implementation of the Spatial–Temporal Graph Convolutional Network (STGCN) for video-based person re-identification, integrating three complementary branches—global, spatial, and temporal—within a unified PyTorch framework. By partitioning frame-level feature maps into horizontal patches and constructing intra-frame and inter-frame graphs, our Spatial GCN branch captures fine-grained body-part structure while the Temporal GCN branch models complementary cues across adjacent frames. A learnable attention mechanism then adaptively fuses global appearance, structural, and temporal embeddings into a final descriptor, which is trained end-to-end with a joint Cross-Entropy and batch-hard triplet loss. Experiments on the MSMT17 dataset demonstrate that our implementation achieves significant gains over the original STGCN baseline—with an mAP of 21.39% and Rank-1 of 11.15%—validating the efficacy of explicit graph modeling and attention-guided feature fusion in handling occlusion, misalignment, and visual ambiguity.

Looking forward, there are several promising directions to further enhance model performance and efficiency. First, exploring adaptive or multi-scale partitioning schemes could allow the network to dynamically adjust patch granularity based on scene complexity. Second, incorporating more expressive graph operators—such as graph attention layers or higher-order spectral convolutions—may improve relational reasoning among non-adjacent patches. Third, sparsity-aware optimization and pruning techniques could reduce the quadratic cost of adjacency computations, enabling real-time inference on longer sequences. Lastly, extending STGCN to leverage auxiliary cues (e.g., pose estimations, depth information) or adopting semi-/unsupervised graph learning paradigms may further boost robustness and generalization in large-scale, unlabeled surveillance scenarios.

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