Empowering Visible-Infrared Person Re-Identification with Foundation Models

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Abstract

Visible-Infrared Person Re-identification (VI-ReID) often underperforms compared to RGB-based ReID due to significant modality differences, primarily caused by the absence of detailed information in the infrared modality. With the development of Large Language Models (LLMs) and Language Vision Models (LVMs), this motivates us to investigate a feasible solution to empower VI-ReID performance with off-the-shelf foundation models. To this end, we propose a novel text-enhanced VI-ReID framework driven by Foundation Models (TVI-FM). The basic idea is to enrich the representation of the infrared modality with automatically generated textual descriptions. Specifically, we incorporate a pretrained multimodal language vision model (LVM) to extract textual features and incrementally fine-tune the text encoder to minimize the domain gap between generated texts and original visual images. Meanwhile, to enhance the infrared modality with text, we employ LLM to augment textual descriptions, leveraging modality alignment capabilities of LVMs and LVM-generated feature-level filters. This allows the text model to learn complementary features from the infrared modality, ensuring semantic structural consistency between the fusion modality and the visible modality. Furthermore, we introduce modality joint learning to align features of all modalities, ensuring that textual features maintain stable semantic representation of overall pedestrian appearance during complementary information learning. Additionally, a modality ensemble retrieving strategy is proposed to consider each query modality for leveraging their complementary strengths to improve retrieval effectiveness and robustness. Extensive experiments demonstrate that our method significantly improves retrieval performance on three expanded cross-modal re-identification datasets, paving the way for utilizing foundation models in downstream data-demanding tasks. The code will be released.

1 Introduction

Person Re-Identification (ReID) aims to retrieve images of the same identity across different cameras, which is crucial for urban security. While RGB-based methods have shown promising results [14, 11, 5, 15, 23], their effectiveness diminishes in low-light conditions at night. To address this issue, Visible-Infrared Person Re-Identification (VI-ReID) [29] is proposed to enable cross-modality retrieval using visible and infrared images, ensuring 24-hour surveillance. Thus this area gains increasing interest among researchers. Infrared images offer an alternative source of visual information to visible images, particularly in low-light conditions. However, there remains a significant disparity between the infrared and visible modalities. Additionally, the absence of detailed information in the infrared modality also presents considerable challenges for existing VI-ReID method [29, 32, 35].

Most existing VI-ReID methods [35, 33, 13, 18, 34, 8, 31] don't take into account the problem of information absence in infrared modality, mostly aim to force the model to focus on mining

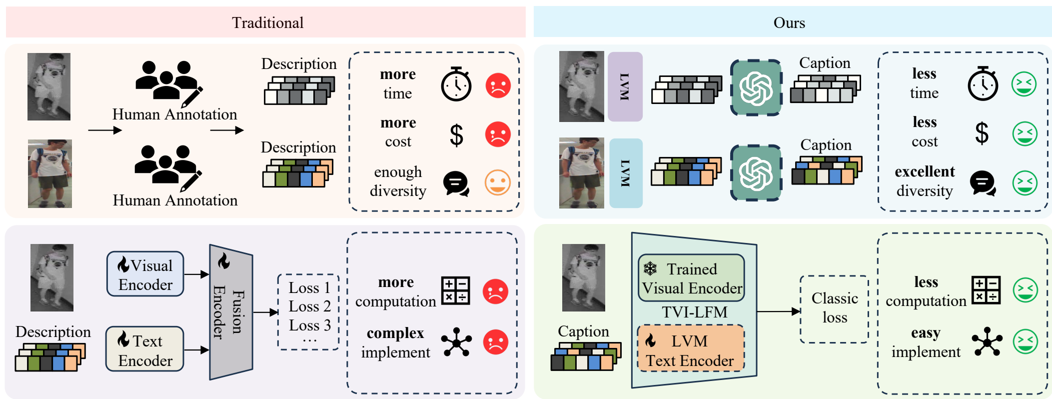


Figure 1: FM improved text-enhanced VI-ReID compared to traditional methods

discriminative information from infrared and visible modalities. Due to the absence of information in infrared modalities, the performance of these methods is limited. There exists methods [6, 40, 4] consider about utilizing auxiliary information like text descriptions or attributes to enhance infrared modality. However, As shown in Figure 1, these methods heavily rely on specially manual annotated auxiliary data, leading to great time and labor cost. Moreover, they struggle to use these auxiliary data with structure with massive learnable parameters and complex metric learning methods, which demands a lot of computation cost. For example, YYDS[6] processes manual annotated coarse descriptions with multiple encoders and complex regularizaton for text-image modality alignment.

Recent advancements in foundation models[2], especially LLM, LVM pre-trained on vast datasets as detailed in 2.2, facilitate customized data generation and augmentation. This further enables effective alignment of textual and visual modality, having great potential to enhance VI-ReID performance with text. This motivates us to investigate a feasible solution to empower the VI-ReID performance with off-the-shelf foundations models. Thus to handle these problems, we introduce a novel Text-enhanced VI-ReID framework driven by Foundation Models (TVI-FM), including Incremental Fine-tuning Strategy (IFS) and Modality Ensemble Retrieving (MER) modules. The basic idea is to enrich the representation of infrared modality with the automatically generated textual descriptions. This expansion method saves considerable time and labor cost for data annotation, which is introduced in Appendix 4.

To address these challenges, we propose a novel Text-enhanced VI-ReID framework, TVI-FM, which incorporates Incremental Fine-tuning Strategy (IFS) and Modality Ensemble Retrieving (MER) modules. This approach significantly reduces the time and labor required for data annotation, as explained in Appendix 4. Specifically, to seamlessly integrate text into existing VI-ReID framework, the Incremental Fine-tuning Strategy (IFS) is proposed to optimize the whole framework. IFS utilizes a pretrained multimodal language vision model (LVM) to extract textual features and incrementally fine-tune the text encoder to minimize the domain gap between generated texts and original visual images. Meanwhile, to enhance the infrared modality with text, we employ LLM to augment textual descriptions, leveraging modality alignment capabilities of LVMs and LVM-generated feature-level filters. This allows the text model to learn complementary features from the infrared modality, ensuring semantic structural consistency between the fusion modality and the visible modality. Furthermore, we introduce modality joint learning to align representations of all modalities, this ensures that textual features uphold stable semantic representation of holistic pedestrian appearance while mining complementary information. Additionally, Modality Ensemble Retrieving (MER) is proposed to enhance retrieval robustness and accuracy by aggregating multiple modalities similarity.

The main contributions can be summarized as follows:

- We propose a novel text-enhanced VI-ReID framework driven by Foundation Models (TVI-FM), which enriches the representation of infrared modality with the automatically generated textual descriptions, reducing the cost of text annotations and enhancing the performance of cross-modality retrieval.
- We develop an Incremental Fine-tuning Strategy (IFS) to employ LLM to augment textual descriptions and incorporate a pre-trained LVM to extract textual features, leveraging modality alignment

capabilities of LVMs and feature-level filters generated by LVMs to enhance infrared modality with information fusion and modality joint learning.

- We introduce Modality Ensemble Retrieving (MER) strategy to comprehensively take into account the queries' similarity with gall features for leveraging their complementary advantages to improve retrieval effectiveness and robustness.
- Extensive experiments demonstrate that our method improves retrieval performance on three expanded cross-modality re-identification datasets, paving the way for utilizing LLMs in downstream data-demanding tasks.

2 Related Work

2.1 Visible-Infrared Person Re-Identification

Visible-Infrared Person Re-Identification (VI-ReID) aims to match identities across visible and infrared images, but facing challenges of significant modality gap and the absence of information in IR modality. Previous works [35, 3, 37, 17, 33] attempt to bridge modality gap by mining discriminative information shared by modalities, but the limited information in blurred IR images results in poor performance. To address these issues, [6] introduces coarse texual descriptions as auxiliary information to enhance cross-modality retrieval. However, it heavily relies on manual annotations, structures with massive learnable parameters and complex metric learning, increasing computational costs and limiting flexibility. Different from existing works, our approach introduces a novel text-enhanced VI-ReID driven by foundation models, which automatically generates semantically rich text to complement visual data. It integrates a textual encoder with excellent capability of text-image alignment and a well-trained visual backbone, incrementally fine-tunes the texual encoder with classical ReID losses. This ensures effective enhancement for existing VI-ReID without additional complex implementations.

2.2 Foundation Model

Foundation models, pre-trained on large and varied datasets, show promise in many fields. Advances in Language-Vision Models (LVMs) like GIT, BLIP, and CLIP, as well as Large Language Models (LLMs) such as GPT-2, GPT-3, Vicuna, and LLaMa2, highlight their data generation and semantic understanding skills. BLIP is adept at creating image-based text descriptions, adaptable to various visual styles. Vicuna, a top LLM, uses its extensive training for complex text adjustments while preserving semantics, suited for custom text enhancements. CLIP's training on vast image-text datasets lets it align these modalities and embed them in a shared semantic space, aiding modality alignment. Our approach leverages these models for automatic text generation and augmentation, and incorporates a pre-trained text encoder into the VI-ReID system to improve performance with textual data.

3 Proposed Method

Our TVI-FM system, as depicted in Fig. 2, leverages Language Vision Models (LVMs) to automatically generate textual modality, which enriches the representations of the infrared modality. This integration leads to significant performance improvements on existing VI-ReID backbones through our Incremental Fine-tuning Strategy (IFS) and Modality Ensemble Retrieving (MER). The IFS is a comprehensive approach that improves the robustness and accuracy of existing VI-ReID systems by complementing the infrared modality with information from generated text. It employs LLM-based Textual Augmentation to diversify textual descriptions while maintaining core semantics, which strengthens the model's resilience to text variability and improves the robustness of extracted textual features. Enhance IR with LVM Generated Filter is used to refine these textual features, focusing on extracting their complementary information according to infrared modality. Modality Joint Learning (MJL) then optimizes the global association of all modalities, aligning semantic representations and preserving the textual semantic of overall pedestrian appearance during complementary information learning. The MER strategy aligns query features from different modalities, capitalizing on their unique strengths to achieve more accurate retrieval. This integrated approach ensures semantic consistency across modalities, maximizing the effectiveness of Information Fusion in capturing complementary information for the infrared modality. As a result, our system advances the capabilities of VI-ReID systems, delivering enhanced performance and semantic understanding.

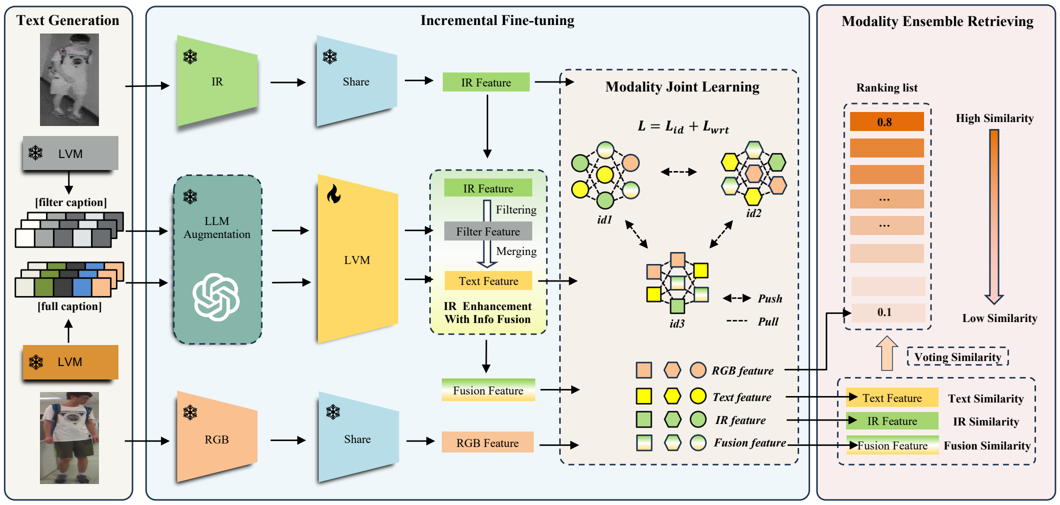


Figure 2: Illustration of TVI-FM: text-enhanced VI-ReID framework integrating a pre-trained LVM textual encoder[24] with a well-trained dual-stream visual backbone[10, 34]. Trained by Incremental Fine-tuning strategy and utilize Modality Ensemble Retreving for robust results.

3.1 Baseline

To seamlessly enhance the performance of existing VI-ReID backbone utilizing textwe employ a frozen well-trained VI-ReID backbone as visual encoder E_v to extract the visual features $f_m = E_v(V_m), m \in \{i, v\}$ from visible images V_r and infrared images V_i respectively, while the text features $f_{t_r} = E_t(T_r)$ are extracted by a textual encoder E_t of LVM from textual descriptions T_r. Benefiting from the image-text pre-training parameters of LVM textual encoder, the text-visual modality gap can be significantly mitigated during training, so we combine text and infrared features using a simple summation-fusion strategy to enhance infrared modality with the complementary information from text, defined as $f_{sum} = f_i + f_{t_r}$. Then we apply the sum of an identity loss and a weighted regularized triplet loss as the total framework:

$$L = L_{id}(f) + L_{wrt}(f) \tag{1}$$

$\boldsymbol{f} \in \{f_r^n\}_{n=1}^{N_r} \cup \{f_{sum}^n\}_{n=1}^{N_{sum}}$ are the extracted features from visible images and the fusion feature composed by infrared feature and corresponding text feature, where $\boldsymbol{N}_r$ denotes the number of visible images, $\boldsymbol{N}_{sum}$ denotes the number of fusion samples.

3.2 Incremental Fine-tuning Strategy

Our Incremental Fine-tuning Strategy (IFS) is a multi-faceted approach designed to enhance the robustness and accuracy of VI-ReID systems through tailored optimization and integration of generated textual and infrared modalities. Through Language Layout Models (LLM) Based Textual Augmentation, we diversify textual descriptions while preserving core semantics, fortifying the model against input variability and enabling the model to extract more robust textual features. Enhance IR with LVM Generated Filter refines textual features, focusing on extracting complementary information for the infrared modality. Modality Joint Learning (MJL) optimizes the global association of all modalities, aligning semantic representations and preventing distortion during fusion feature learning. This comprehensive strategy ensures semantic consistency across modalities, maximizing the effectiveness of Information Fusion in capturing complementary information for infrared modality, thus advancing the capabilities of VI-ReID systems.

3.2.1 LLM based Textual Augmentation

To ensure getting robust representations from diverse generated textual descriptions to enhance VI-ReID model, while preserving semantic integrity, we implement a probabilistic augmentation module based on LLM. This module regenerates more diverse descriptions for the same target and prevents overfitting to incidental information in sentences apart from the core features of person appearance, such as sentence style. In detail, given an original description $\boldsymbol{T}$, the module employs an LLM to augment the textual descriptions, controlled by the prompt ***"Rephrase the person's description using similar words, without changing the original semantics."*** The transformation is applied as follows:

$$T^* = \begin{cases} LLM(T \mid \text{Prompt}), & \text{with probability } p \\ T, & \text{with probability } (1-p) \end{cases} \tag{2}$$

where $p = 0.5$ reflects the assumption that each description variant is equally probable. Utilizing the powerful customized text understanding and generation capability of LLM, this approach not only diversifies the textual descriptions but also maintains their essential meanings. This forces the model to focus on extracting the core semantic of person appearance, thus enhancing the robustness of our system against text variability. Moreover, we can apply this augmentation method directly on existing framework related with text data, without any change of the original structure.

3.2.2 Enhance IR with LVM Generated Filter.

Through the LLM based textual augmentation, our textual encoder can extract more robust representations from the diverse textual description, containing rich complementary semantic compared to the infrared images. In order to fully mine the complementary semantic for infrared modality from auxiliary text data, which has been aligned with image modality in pre-train stage, we develop a novel feature-level information filtering mechanism to filter the redundant semantics in textual representations that are as same as infrared images. To get the filter features with semantic contained by infrared, we employ the fine-tuned LVM in Section A to generate textual description T_i from infrared images V_i as filter features, the generation of the filter features $\boldsymbol{f}_{t_i}$ can be represented as $\boldsymbol{f}_{t_i} = LVM(V_i)$. Considering that the fusion features $\boldsymbol{f}_{sum}$ are conbined with text features $\boldsymbol{f}_{t_r}$ and infrared features $\boldsymbol{f}_i$, which contains the same redundant semantic of the person appearance and may affect the semantic structural consistency with features of other modalities. With the proposed filter text features $\boldsymbol{f}_{t_i}$, we can obtain the refined text features by directly subtracting filter features, containing rich complementary information for infrared modality. So we form the fusion features jointly with the refined text features and infrared features. In detail, the refined fusion features can be represented as:

$$\boldsymbol{f}_{sum} = \boldsymbol{f}_i + \boldsymbol{f}_{t_r} - \boldsymbol{f}_{t_i} \tag{3}$$

Then we can force our model to focus on learning complementary information by solely fine-tuning the filtered text features without other redundant information.

3.2.3 Modality Joint Learning

In corperating with the learning of complementary information in Section 3.2.2, we introduce the Modality Joint Learning (MJL) strategy. The filter mechanism focuses on refining textual representations to capture complementary information for the infrared modality, while MJL optimizes the global association of all modalities. By jointly optimizing the total framework with visible, infrared, textual, and fusion modalities, MJL aligns corresponding semantics across all modalities, which enhances semantic consistency in textual representations and provides more informative hard samples for multi-modal representation learning. This maximizes the effectiveness of Information Fusion in capturing complementary information for the infrared modality while preventing potential semantic distortion during fusion feature learning. In detail, we jointly optimize the total framework with visible features $\boldsymbol{f}_r$, infrared features $\boldsymbol{f}_i$, textual features $\boldsymbol{f}_{t_r}$, fusion modality $\boldsymbol{f}_{sum}$ by the combination of cross-entropy loss L_{id} and weighted regularized triplet loss L_{wrt}:

$$L^* = L_{id}(f^*) + L_{wrt}(f^*) \tag{4}$$

In our training loss L^*, all the feature $\boldsymbol{f^*} \in \{f_r^n\}_{n=1}^{N_r} \cup \{f_i^n\}_{n=1}^{N_i} \cup \{f_{t_r}^n\}_{n=1}^{N_{t_r}} \cup \{f_{sum}^n\}_{n=1}^{N_{sum}}$ from different modalities share the same classifier and the global distance association with any other feature is also optimized, where $\boldsymbol{N}_r$ denotes the number of visible images, $\boldsymbol{N}_{sum}$ denotes the number of fusion samples, $\boldsymbol{N}_i$ denotes the number of infrared samples, $\boldsymbol{N}_t$ denotes the number of textual samples.

3.3 Modality Ensemble Retrieving

To maximize utilization of query representations with rich semantics mined from Incremental Fine-tuning Strategy in Section 3.2 for more accurate retrieval, the Modality Ensemble Retrieving (MER) strategy is employed to comprehensively take into account the unique and complementary advantages

Table 1: Ablation study on **Infrared** query enhanced by **auxiliary textual descriptions** ($\boldsymbol{I}+\boldsymbol{T} \rightarrow \boldsymbol{R}$) about each component on the performance of **Tri-SYSU-MM01** and **Tri-LLCM** datasets. **Rank** (R) at first accuracy (%), **mAP**(%), and **mINP**(%) are reported.

$I+T \rightarrow R$					Tri-SYSU-MM01			Tri-LLCM		
B	Filter	MJL	LLM	MES	R1	mAP	mINP	R1	mAP	mINP
✓					72.52	69.15	55.93	52.63	58.82	55.43
✓	✓				77.00	73.73	61.50	54.73	60.95	57.64
✓	✓	✓			83.97	80.40	69.46	56.76	63.58	60.35
✓	✓	✓	✓		84.17	80.72	70.02	57.13	64.06	60.72
✓	✓	✓		✓	84.88	81.32	70.57	57.09	63.87	60.62
✓	✓	✓	✓	✓	**84.90**	**81.47**	**70.85**	**58.19**	**65.08**	**61.83**

of different modalities. This involves averaging the features from infrared modality $\boldsymbol{f}_i$, textual modality $\boldsymbol{f}_{t_r}$, and fusion modality $\boldsymbol{f}_{sum}$ to form a comprehensive query feature:

$$\boldsymbol{f}_{agg} = mean(\boldsymbol{f}_i, \boldsymbol{f}_{t_r}, \boldsymbol{f}_{sum}) \tag{5}$$

Fusion features $\boldsymbol{f}_{sum}$ provide a comprehensive and enriched description of the target and aims to learn features with the same semantic structure of RGB modality, serving as the primary matching modality. ***Infrared features*** $\boldsymbol{f}_i$ provide valuable and contiguous visual semantics. Their similarity with RGB images can serve as a supplementary reference for visual information. ***Textual features*** $\boldsymbol{f}_{t_r}$ provide descriptive details that may not be visually apparent or recognizable in infrared images. The degree of similarity between textual features and RGB images serves as a explicit reference for the missing or blurred appearance information in the infrared modality. ***The comprehensive features*** $\boldsymbol{f}_{agg}$ used to retrieve RGB features $\boldsymbol{f}_r$ integrate the similarity scores of multiple query modalities with RGB to obtain a voting score, effectively harness the complementary strengths of each modality and reduce the potential impact of extreme scores in the fusion query retrieval list, enhancing the overall effectiveness and robustness of the retrieval system.

4 EXPERIMENTS

4.1 Experimental Settings

Datasets. We evaluate our framework on the expanded datasets, including Tri-SYSU-MM01, Tri-RegDB, and Tri-LLCM. The proposed three multi-modal datasets with text description for each image are expanded from original visible-infrared images datasets SYSU-MM01[30], RegDB[20], and LLCM[38] by the fine-tuned generative LVMs named Blip[16] in three stages (Detail in Appendix A). The splits of the training set and testing set for each dataset are available in Appendix G.

Evaluation Protocols. In line with established VI-ReID settings [36, 33], we assess performance of infrared query mode and textual enhanced infrared query mode using Rank-k matching accuracy, mean Average Precision (mAP), and mean Inverse Negative Penalty (mINP[36]) within our TVI-FM framework. To get stable performance on SYSU-MM01 and LLCM, we evaluate our model for 10 times with random split of the gallery set, as for RegDB we evaluate our model on the 10 trials with different training/testing splits. Finally we report our model's average performance on each dataset. The task settings with detail of different query modes are shown in Appendix C.

Implementation Overview. We utilize a dual-stream resnet-50[34] pretrained on ImageNet[25] as the visual backbone and a transformer in CLIP[24] for the textual backbone. Training involves of visible and infrared images alongside text descriptions generated from these images, which are augmented by vicuna-7b[41] with a probabilistic rephrasing strategy. Incremental fine-tuning is applied by fixing the visual parameters and only tuning the texual part of the framework. All Details are described in Appendix B.

4.2 Ablation Study

To thoroughly evaluate the effect of each component to our proposed method, we conduct comprehensive ablation studies on the Tri-LLCM and Tri-SYSU-MM01 datasets. These studies involved gradually adding the proposed modules on our baseline, systematically removing specific modules

Table 2: The influence of whether to froze visual backbone on case of infrared query ($\boldsymbol{I} \rightarrow \boldsymbol{R}$) and fusion query($\boldsymbol{I} + \boldsymbol{T} \rightarrow \boldsymbol{R}$) on the performance of **Tri-SYSU-MM01** and **Tri-LLCM**. In order to focus on the impact of IFS on the learning of infrared features and fusion features separately, we **remove** the **MES** strategy for fusion query to avoid the effect of aggregating original information from infrared modality and text modality together with fusion modality.

$I \rightarrow R$	Tri-SYSU-MM01			Tri-LLCM		
	R1	mAP	mINP	R1	mAP	mINP
VI-ReID Backbone	69.89	66.74	53.34	53.53	59.77	56.40
Ours - Frozen	64.46↓**5.43**	61.31↓**5.43**	46.94↓**6.40**	49.29↓**4.24**	55.78↓**3.99**	52.12↓**4.28**

$I + T \rightarrow R$	Tri-SYSU-MM01			Tri-LLCM		
	R1	mAP	mINP	R1	mAP	mINP
Ours	**84.17**	**80.72**	**70.02**	**57.13**	**64.06**	**60.72**
Ours - Frozen	84.03↓**0.14**	79.85↓**0.87**	68.06↓**1.97**	55.47↓**1.66**	62.23↓**1.83**	58.86↓**1.86**

from our framework and assessing the impact on its performance. The overall experimental setup remained consistent, with only the module under evaluation being modified.

Effect of Enhancing IR with LVM Generated Filter. In order to enhance the semantic uniformity of fusion queries and other modalities while filtering out redundant information, we implement a feature-level filtering mechanism utilizing a Language Vision Model [16] to generate the filter features from IR images. Compared with the baseline, the filter module achieves enhancement of the comprehension of the textual complementary semantic, while the baseline cannot extract enough effective feature from text very well. The method obtains 4.48% Rank-1 improvement in Tri-SYSU-MM01 and 1.90% Rank-1 improvement in Tri-LLCM respectively in Table 1.

Effect of Modality Joint Learning. For fully making use of the multi-modal representations and learn robust, deeply aligned and semantic-consistent features for each identity, we propose a global modality joint learning method to incorporating with the filter mechanisms. Based on the experiment result in Table 1, compared to baseline only with filter mechanisms, adding this method gains a great enhancement of 6.97% Rank-1 improvement, 6.67% mAP improvement, 7.96% mINP% improvement in Tri-SYSU-MM01 and 2.03% Rank-1 improvement, 2.63% mAP improvement, 2.71% mINP improvement in Tri-LLCM.

Effect of Modality Ensemble Retrieving. The Modality Ensemble Searching strategy fully take account into all query modalities, minimizing the potential impact of extreme scores with a comprehensive query representation. From Table 1, it can be observed that incorporating MES provides an additional improvement of 0.71% in Rank-1, 0.60% in mAP, and 0.55% in mINP in the Tri-SYSU-MM01 dataset over the joint learning method with filter mechanisms. Similarly, on the Tri-LLCM dataset, MES achieves a 1.10% Rank-1 improvement, 1.21% mAP improvement, and 1.21% mINP improvement. These results demonstrate that the aggregation of different query modality leads to better overall performance, enabling more accurate retrieval.

Effect of LLM based Textual Augmentation. To extract more robust representations from diverse textual descriptions for the same person against the potential over-fitting while maintaining semantic integrity. We implement a probabilistic augmentation module based on Large Language Model (LLM). With LLM based augmentation, as the result shown in Table 1, it further improves our model's performance assisted with auxiliary text, and it can works well with other modules, achieving 84.90% Rank-1 and 58.19% Rank-1 in Tri-SYSU-MM01 and Tri-LLCM respectively.

Discussion of Frozen Operation It's important for VI-ReID system to handle cases with auxiliary text descriptions and without them in uncertain real scenarios application. When we allow the visual backbone to update parameters, as shown in Table 2, performance with infrared query suddenly declines by 5.43% and 4.24% of Rank-1 in the two datasets respectively. The performance on fusion query ($I + T \rightarrow R$) is also affected, with a decline of 0.14% Rank-1 in Tri-SYSU-MM01 and 1.66% Rank-1 in Tri-LLCM. This demonstrates the importance of freezing the integrated backbone to avoid the potential performance influence caused by conflict of infrared feature learning and fusion feature learning during training. With Frozen Operation we can seamlessly enhancing existing VI-ReID framework by only fine-tuning textual encoder.

Table 3: Compare with the state-of-the-art methods on the proposed Tri-SYSU-MM01

Methods	Venue	Type	All Search			Indoor Search		
			R-1	mAP	mINP	R-1	mAP	mINP
Zero-Padding [29]	ICCV-17		14.80	15.95	-	20.58	26.92	-
HCML [32]	AAAI-18		14.32	16.16	-	24.52	30.08	-
cmGAN [22]	IJCAI-18		26.97	27.80	-	31.63	42.19	-
AlignGAN [28]	ICCV-19		42.40	40.70	-	45.90	54.30	-
AGW [35]	TPAMI-21		47.50	47.65	35.30	54.17	62.97	59.23
DDAG [34]	ECCV-20		54.75	53.02	39.62	61.02	67.98	62.61
CM-NAS [9]	ICCV-21		61.99	60.02	-	67.01	72.95	-
DART [31]	CVPR-22	$I \rightarrow R$	68.7	66.3	-	82.0	73.8	-
CAJ [33]	ICCV-21		69.88	66.89	53.61	76.26	80.37	76.79
PAENet [1]	MM-22		74.22	73.90	-	78.04	83.54	-
DEEN [38]	CVPR-23		74.70	71.80	-	80.30	83.30	-
SAAI [7]	ICCV-23		75.90	77.03	-	83.20	88.01	-
MSCLNet [37]	ECCV-22		76.99	71.64	-	78.49	81.17	-
SGIEL [8]	CVPR-23		77.12	72.33	-	82.07	82.95	-
PartMix [13]	CVPR-23		77.78	74.62	-	81.52	84.38	-
YYDS[6]	Arxiv-24	$I + T \rightarrow R$	74.60	70.35	56.01	81.35	83.64	79.56
VI-ReID Backbone	-	$I \rightarrow R$	69.89	66.74	53.34	76.91	80.64	76.70
TVI-FM	-	$I + T \rightarrow R$	**84.90**	**81.47**	**70.85**	**89.06**	**90.78**	**88.39**

Table 4: Compare with the state-of-the-art methods on the proposed Tri-RegDB and Tri-LLCM

Methods	Venue	Type	Tri-RegDB			Tri-LLCM		
			R-1	mAP	mINP	R-1	mAP	mINP
DDAG [34]	ECCV-20		68.06	61.80	48.62	40.3	48.4	-
AGW [35]	TPAMI-21		70.49	65.90	51.24	43.6	51.8	-
CAJ [33]	ICCV-21	$I \rightarrow R$	84.8	77.8	61.56	48.8	56.6	-
DART [31]	CVPR-22		82.0	73.8	-	52.2	59.8	-
MMN [39]	MM-21		87.5	80.5	-	52.5	58.9	-
DEEN [38]	CVPR-23		89.5	83.4	-	54.9	62.9	-
YYDS[6]	Arxiv-24	$I \rightarrow R$	90.95	84.22	70.12	58.13	64.91	61.77
VI-ReID Backbone	-	$I \rightarrow R$	89.51	83.51	69.65	53.53	59.77	56.40
TVI-FM	-	$I + T \rightarrow R$	**91.38**	**85.92**	**72.73**	**58.19**	**65.08**	**61.83**

4.3 Comparison with the State-of-the-art Methods

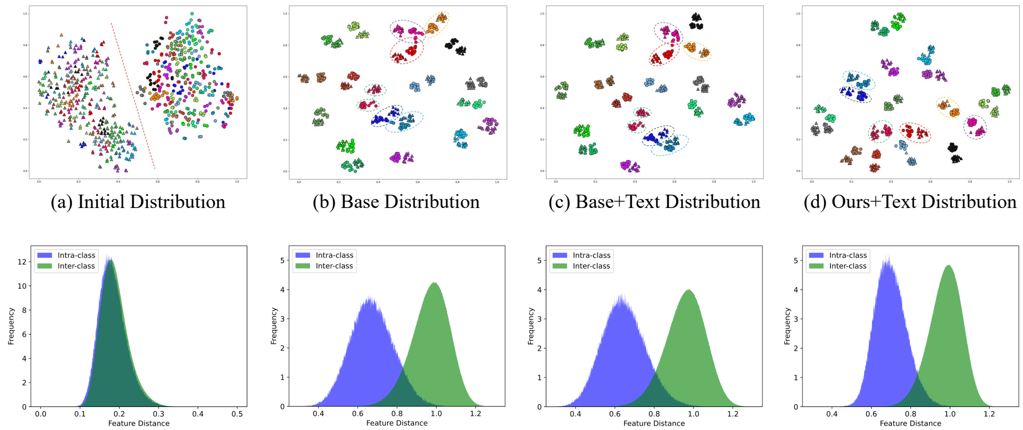
In this section, we present a comprehensive comparison of the proposed TVI-FM, against state-of-the-art models across different datasets as outlined in Table 3 and Table 4. Our evaluation includes a variety of metrics: Rank-1 (R-1), mean Average Precision (mAP), and mean Inverse Negative Penalty (mINP).

Performance on Tri-SYSU-MM01 Dataset As shown in Table3, with auxiliary textual descriptions, TVI-FM outperforms all previous methods under 'All Search' and 'Indoor Search' conditions. Specifically, TVI-FM achieves a significant improvement in Rank-1, reaching 84.90% and 89.06% respectively, compared to the next best result of 77.78% by PartMix in All Search and 82.07% by SGIEL in Indoor Search. Furthermore, in terms of mAP, TVI-FM posts scores of 81.47% and 90.78% which is a substantial increase from the previous high scores of 77.03% and 88.01%, respectively.

Performance on Tri-RegDB and Tri-LLCM Dataset Table 4 outlines our method's performance on the two datasets. In the Tri-RegDB dataset, TVI-FM obtains an Rank-1 of 91.38% and mAP of 85.92%, higher than the prior top scores of 90.95% in Rank-1 and 84.22% in mAP by YYDS. In the Tri-LLCM dataset, our method leads with an Rank-1 of 58.19% and mAP of 65.08%, surpassing the prior top scores of 58.13% in Rank-1 and 64.91% in mAP, both held by YYDS.

4.4 Visualization

Feature Distribution Visualization. To explore the reason why our method is effective, we utilize t-SNE[27] 2D feature space and visualize cosine distances of the intra-class and inter-class on the proposed Tri-SYSU-MM01 dataset in Fig.3. From the 'Initial' to 'Ours+Text' in 3(a-d), the t-SNE



(a) Initial Distribution (b) Base Distribution (c) Base+Text Distribution (d) Ours+Text Distribution

(e) Initial Distance (f) Base Distance (g) Base+Text Distance (h) Ours+Text Distance

Figure 3: Figures in the first row (a-d) show the t-SHE feature distribution of the 20 randomly selected identities, triangle means infrared features(w/wo textual fusion) and circle means visible features. Different colors indicate different identities. Figures in the second row (e-h) represent the intra-class(blue) and inter-class(green) distance of infrared features(w/wo textual fusion) and visible features.

feature distribution shows that with textual assistance, our method greatly enhances the ability of distinguishing features from different identities and reduces extreme outliers of the same identity and samples with too large cross modal discrepancy. While for feature distance distribution in 3(e-h), corresponding to 2D t-SHE[27] feature distribution, the inter/intra-class distance distributions are increasingly sparated well, especially, the situation of excessive intra-class distance has also been greatly reduced.

Retrieval Result. To intuitively present the performance of our method, we visualize some retrieval results of the Base VI-ReID model, Text-assisted base model and our method with text on the Tri-SYSU-MM01 dataset in Appendix F. For the same query image, with assistance of text description, the base model does a slightly better job of identifying samples that more closely correspond to the original RGB image, but there are still other identities in the results. Our method can mine the rich complementary information contained in text data to the maximum extent, the modality fusion greatly enhances the retrieval performance at fine-grained semantic level, even the failed retrieval samples still have high similarity with the target identity.

5 Conclusion

This paper proposes a novel framework of text-enhanced VI-ReID driven by Foundation Models (TVI-FM). VI-ReID often lags behind RGB-based ReID due to the inherent differences between modalities, particularly the absence of information in the infrared modality. Our method enriches the representation of the infrared modality by integrating automatically generated textual descriptions and augments them with LLM. We utilize a pretrained multimodal LVM to extract textual features and fine-tune the text encoder to minimize the domain gap between generated texts and original visual images. Leveraging LVMs' modality alignment capabilities and feature-level filters, this approach enables the text model to learn complementary features from the infrared modality, ensuring semantic structural consistency between the fusion modality and the visible modality. We further introduce modality joint learning to align features of all modalities, ensuring stable semantic representation of overall pedestrian appearance during complementary information learning. Moreover, a modality ensemble retrieving strategy is proposed to leverage the complementary strengths of each query modality, enhancing retrieval effectiveness and robustness. Extensive experiments on three expanded cross-modal re-identification datasets demonstrate significant improvements in retrieval performance, paving the way for utilizing foundation models in downstream data-demanding tasks.

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A Datasets Expansion

Given that there are almost no publicly available large-scale RGB-Text-Infrared person re-identification datasets up to now. The only existing VI-ReID dataset with text is labeled manually, YYDS[6] using only one Coarse description for all images with the same identity, which probably causes serious overfitting and cannot deal with the complex and various description in the real-world application. In order to get text data with various styles and rich semantic detail like for every RGB and IR image without any manual annotation, We construct three multi-modal dataset called Tri-SYSU-MM01, Tri-LLCM and Tri-RedDB from the original datasets SYSU-MM01[30], LLCM[38], RegDB[20] separately, following steps below:

1) Getting the LVM able to Generate Textual description from RGB images: We pre-trained Blip[16] on a large-scale pedestrian image-text dataset [26] to get the captioner for RGB modality.

2) Getting the LVM able to Generate Textual description from IR images: Firstly utilize the captioner for RGB modality we got before to generate textual descriptions from visible images in SYSU-MM01's training split, which contains various visible and infrared images for every identity. Then we remove rgb modal-related terms from these generated text by regular expression filter, build an IR-Text(filtered) dataset according to the same identity label shared by filtered text descriptions and infrared images. Finally we fine-tune the Blip[16] got from **step 1** on the IR-Text(filtered) dataset, get the captioner for IR modality

3) Getting Textual description from any dataset contains visible-infrared images: Utilize the refined LVM respectively we get in former steps as captioners for RGB modality and IR modality, to zero-shot generate text descriptions for datasets containing visible-infrared images.

The statisctics of our expanded dataset Tri-LLCM, Tri-RegDB and Tri-SYSU-MM01 are shown in Table 5. And the visualization on samples of our datasets are shown in 4

Table 5: Dataset statistics

Datasets	#ID	#RGB	#IR	#Text
Tri-LLCM	1064	25626	21141	46767
Tri-RegDB	412	4120	4120	8240
Tri-SYSU-MM01	491	30071	15792	45863

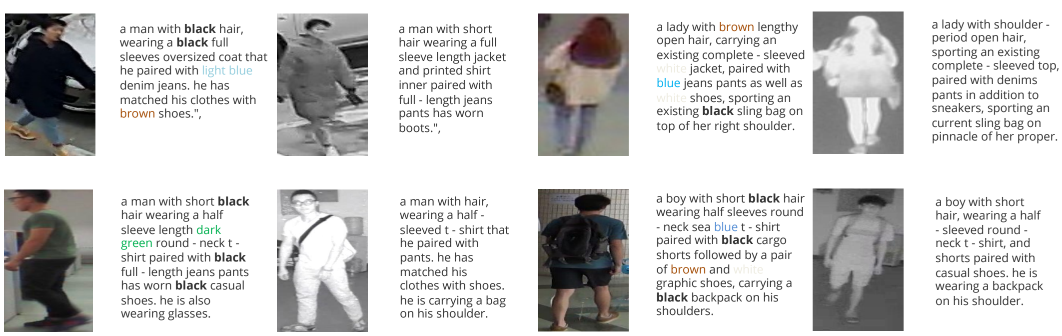

Figure 4: Visualization of the data samples selected from the expanded three datasets.

B Implementation Details

We implement our framework in PyTorch [21] utilizing a single NVIDIA RTX 3090 GPU for training. For visual backbone training, it takes about 9GB memory for training and about 3GB memory for testing, about 9 hours are needed for training on Tri-SYSU-MM01 and Tri-LLCM, about 1 hour for smaller Tri-RegDB. For incremental fine-tuing, it takes about 5GB memory for training and about 3GB memory for testing, about 1 hour are needed for fine-tuning on Tri-SYSU-MM01 and Tri-LLCM, about 10 miniutes for smaller Tri-RegDB. Each batch consists of 8 identities, with each identity containing 4 visible images, 4 infrared images, 4 text descriptions generated from visible images, and 4 text descriptions generated from infrared images. All input images are resized to 3 $\times$ 288 $\times$ 144, with full augmentation strategy as the same as CAJ [33]. All text descriptions are augmented by the proposed LLM rephrasing augmentation with a probability of 0.5, here we use vicuna-7b [41] as our LLM model. We employ a dual-stream resnet50 model [34] pre-trained on ImageNet [25] as the visual backbone and a transformer model with parameters derived from CLIP [24] as the textual backbone. For incrementally fine-tuning our TVI-FM, firstly we should get an available well-trained visual backbone. Here we utilize the augmentation method [33] to train the visual backbone for 120 epochs by cross-entropy loss and weighted regularized triplet loss, finally get the well-trained visual backbone. Then we integrate the well-trained VI-ReID model and fine-tune the textual backbone and a simple ReID bottleneck[19] applied for each feature for 20 epochs. We use the Adam[12] for optimization. For the Tri-SYSU-MM01 and Tri-LLCM datasets, in both visual and textual parts, the learning rate is set to 3.5e-4 and the weight decay to 5e-4. For the Tri-RegDB dataset, the learning rate for the visual part is 2e-3 with weight decay of 5e-4, and for the textual part, the learning rate is 1e-5 with weight decay of 4e-5. The learning rate rises up to the initial value by a linear warm-up scheme for the first 10 epochs, then decays by a linear scheme with a decay-factor of 0.1 at the milestones of 40, 60, and 100 epochs.

C Task Settings

C.1 Setting Details

We define $\mathcal{R} = \{V_r^n\}_{n=1}^{N^r}$ and $\mathcal{I} = \{V_i^n\}_{n=1}^{N^i}$ as the samples for visible and infrared images respectively, where each V_r^n and V_i^n represents an individual image from the visible and infrared modality. Textual descriptions $\mathcal{T}_r = \{T_r^n\}_{n=1}^{N^r}$ are autonomously generated for the visible images using a Language Vision Model (LVM). These descriptions provide detailed semantic insights about the identities, depicted across various textual styles. $N_v = N^r + N^i$ indicate the total numbers of samples in each modality. The identity labels for these images are given by $\mathcal{Y}^r = \{y_r^n\}_{n=1}^{N^r}$ for visible images and $\mathcal{Y}^i = \{y_i^n\}_{n=1}^{N^i}$ for infrared images. The task aims to retrieve visible representations $G^r = \{f_r^n\}_{n=1}^{N^r}$ through the infrared representations $Q^i = \{f_i^n\}_{n=1}^{N^i}$ or infrared representations enhanced by text representations $Q^t = \{f_{t_r}^n\}_{n=1}^{N^i}$. Inference is performed in two modes: one involves using a **fusion query**, as the same as the real-world conditions that descriptions provided by witnesses for the same target are diverse, each query $q_{sum} = \{f_i, f_{t_r}\}, f_i \in Q^i, f_{t_r} \in Q^t$ is composed by a infrared feature f_i and a corresponding randomly selected feature f_{t_r} of textual description. The other mode uses solely an **infrared query** $q_i = \{f_i\}, f_i \in Q^i$. The system then computes a ranking list based on the similarity of each query feature to gallery features $g = \{f_r\}, f_r \in G^r$ in visible modality, in order to find out all the person with the same identity.

D limitations and future research

While the TVI-FM framework has shown promising outcomes, two limitations still remain: 1)Its performance is linked to the quality of textual descriptions. High-quality textual descriptions will improve the accuracy of retrieval, which plays a crucial role in driving performance improvements in our framework. 2)Challenges persist in effectively handling challenging datasets such as LLCM[38]. Future researches on LLM and LVM is expected to generate higher-quality textual descriptions. Leveraging these advancements could lead to more robust and accurate retrieval results.

E Broader Impacts

Our TVI-FM framework offers significant advancements in urban security by enhancing person re-identification in low-light conditions, boosting surveillance effectiveness. It automates text generation from IR and RGB images, reducing annotation workload and improving text robustness, aiding multi-modal research and smart security system development. However, it's crucial to address environmental impact concerns related to large models' energy consumption and the privacy risks associated with re-identification technology. Governments and regulatory bodies must enact stringent regulations to prevent misuse and ensure identification accuracy to avoid societal disruptions.

F Retrieve Result Examples w/wo Text

Figure 5: Visualization of the rank-5 retrieval results obtained by the base model and our model on the proposed Tri-SYSU-MM01 dataset.

G Assets Details

This section provides the necessary details for the data assets utilized in our research: SYSU-MM01, LLCM, and RegDB.

- **SYSU-MM01**[30]
  - *Source and Citation*: The SYSU-MM01 dataset was created by researchers at Sun Yat-sen University (SYSU). Ancong Wu, et al. “RGB-IR Person Re-Identification by Cross-Modality Similarity Preservation” (2020) is the seminal paper associated with this dataset.
  - *data splits*: The training set contains 22,258 visible images and 11,909 infrared images of 395 identities. The testing set contains 96 identities, with 3,803 infrared images for query and 301 (single-shot) randomly selected visible images as the gallery set.
  - *URL*: The dataset can be accessed through a GitHub repository: `https://github.com/wuancong/SYSU-MM01` , where users must agree to the data release agreement.
  - *License*: We cannot find out the license SYSU-MM01 uses, but the author requires signing the usage agreement notice and contact him through e-mail to get the dataset. The detailed usage agreement refers to the github url mentioned above.
- **LLCM**[38]
  - *Source and Citation*: The LLCM dataset was introduced by researchers from Xiamen University. Yukang Zhang and Hanzi Wang’s paper “Diverse Embedding Expansion Network and Low-Light Cross-Modality Benchmark for Visible-Infrared Person Re-identification” (2023) discusses this dataset.
  - *data splits*: The training set contains 30,921 images of 713 identities, and the test set contains 13,909 images of 351 identities.
  - *URL*: The dataset is available on GitHub `https://github.com/ZYK100/LLCM`.
  - *License*: CC-BY 4.0
  - *Code*: We use its code for feature visualization.
- **RegDB**[20]
  - *Source and Citation*: The RegDB dataset was developed at Dongguk University from the paper named "Person Recognition System Based on a Combination of Body Images from Visible Light and Thermal Cameras".
  - *data splits*: The training set contains 206 identities and the testing set contains 206 identities. There are 10 visible images and 10 infrared images for each person.
  - *URL*: We can only find the paper’s doi `https://doi.org/10.3390/s17030605`
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