Empowering Visible-Infrared Person Re-Identification with Foundation Models

Zhangyi Hu[1*] **Bin Yang**[1] **Mang Ye**[1†]
[1]National Engineering Research Center for Multimedia Software, Institute of Artificial Intelligence,
Hubei Key Laboratory of Multimedia and Network Communication Engineering,
School of Computer Science, Hubei Luojia Laboratory, Wuhan University, Wuhan, China.
{zhangyi_hu,yangbin_cv,yemang}@whu.edu.cn

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. The development of foundation models like Large Language Models (LLMs) and Language Vision Models (LVMs) motivates us to investigate a feasible solution to empower existing VI-ReID backbones 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 textual descriptions automatically generated by LVMs. Specifically, we incorporate a pre-trained LVM to extract textual features from descriptions generated by two modal-specialized fine-tuned LVM captioners and augmented by LLM. To enrich infrared features with generated textual information, we use modality alignment capabilities of LVMs and LVM-Generated feature-level filters to create a preliminary fusion modality. This enables the text model to learn complementary features according to the infrared modality, ensuring semantic consistency between the fusion and visible modalities. Then, modality joint learning aligns features of all modalities, incrementally fine-tunes text encoder to adapt to frozen VI-ReID backbone, maintaining stability of overall semantic of text representations while refining text-enriched infrared representations, thus minimizing the domain gap between enriched infrared and visible modalities. Additionally, Modality Ensemble Retrieving is proposed to leverage complementary strengths of each query modality to improve retrieval performance 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 [16, 13, 7, 17, 24], their effectiveness diminishes in low-light conditions at night. Infrared images provide a valuable visual alternative to visible images in low-light scenarios. Various techniques [**?** 39] have been proposed for visible-infrared person re-identification (VI-ReID), ensuring 24-hour surveillance. However substantial differences exist between infrared and visible modalities. This disparity mainly caused by the lack of detail in infrared images, poses significant challenges for current VI-ReID methods [33, 36, 39].

Most existing VI-ReID methods [39, 37, 15, 20, 38, 10, 35] do not adequately address the issue of information absence in the infrared modality. Instead, they primarily focus on extracting discriminative information shared between the infrared and visible modalities. However, the lack of information in

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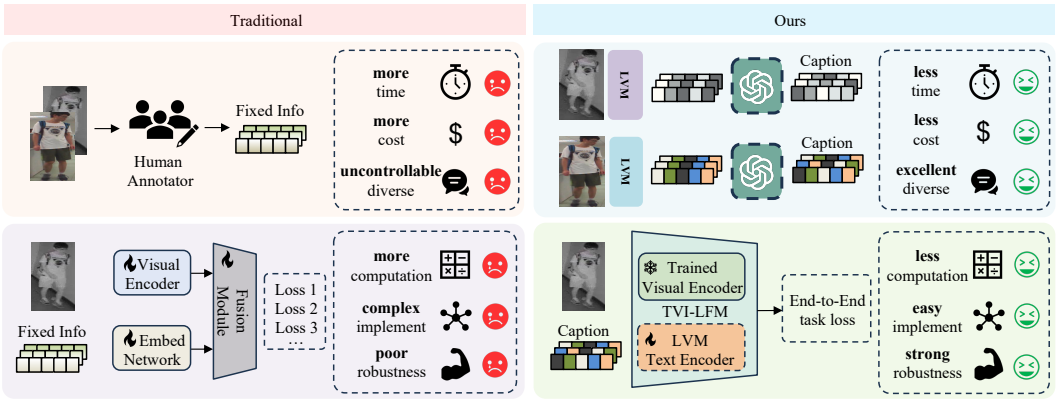


Figure 1: text-enhanced VI-ReID driven by foundation models compared to traditional methods

the infrared modality limits the performance of these methods. There also exist methods [8, 43, 5] that utilize auxiliary information like text descriptions [8] or attributes [43, 5] to enhance the infrared modality. However, as shown in Fig. 1, these methods heavily rely on human-annotated data, leading to significant time, labor costs and uncontrollable data quality. Moreover, due to neglecting the natural semantic connection between the auxiliary and visual modalities, they struggle to leverage the auxiliary data to enhance the VI-ReID task. Additionally, they rely on prior knowledge [8], complex model structures [8, 5], or manually designed loss functions [43] to extract auxiliary information, requiring training the whole framework from scratch to adapt the new information. These approaches cannot deal with the model's sensitivity to auxiliary data variations that may appear in real scenarios and result in considerable computational costs and limited performance.

Recent advancements in foundation models [2], particularly LLMs and LVMs, demonstrate strong inherent capabilities for text-visual modality alignment and personalized data generation, built on the extensive prior knowledge and powerful representation ability acquired during pre-training on vast datasets. Leveraging these capabilities, foundation models can automatically generate text from images and semantically link language with vision, providing vital complementary information for the infrared modality. This can effectively compensate for informational absence in infrared modality compared to the visible modality, thus bridging the gap between them. Motivated by this potential, to handle the challenges mentioned before, we introduce the Text-enhanced VI-ReID framework driven by Foundation Models (TVI-FM). This framework aims to seamlessly integrate auxiliary information into existing VI-ReID systems using off-the-shelf models, enhancing their overall performance by enriching the representation of the infrared modality with automatically generated textual descriptions. It comprises Modal-Specific Caption (MSC), Incremental Fine-tuning Strategy (IFS), and Modality Ensemble Retrieving (MER). Specifically, MSC is proposed to automate the generation of diverse textual descriptions from original infrared and visible image datasets. Initially, we pre-train a generative LVM on a massive pedestrian image-text dataset [28]. Using this model, we expand the text modality for randomly selected visible-infrared image pairs by generating descriptions from visible images and subsequently removing color-specific terms to create infrared-text pairs. These adapted pairs are then used to fine-tune a second model, resulting in two specialized models capable of producing accurate textual descriptions for both infrared and visible images. Additionally, to further enhance the textual quality and diversity, we employ an LLM to perform random paraphrasing augmentation on the generated text during the training process. This approach significantly reduces manual annotation efforts and improves the architecture's robustness against text variations. To enhance the utilization of auxiliary information generated by MSC, we introduce the Incremental Fine-tuning Strategy (IFS), which comprises Semantic Filtered Fusion (SFF) and Modality Joint Learning (MJL). SFF extracts features from text generated based on visible-infrared image pairs. Visible-derived textual features are then semantically filtered using infrared-derived textual features and combined with infrared visual features, enabling us to selectively merge the infrared modality and its complementary information. This process leverages the intrinsic language-vision alignment capabilities of foundational models to create preliminary fusion features sharing a similar semantic structure with visible modalities, setting the stage for further feature refinement. Built on this, MJL further refines these enhanced infrared features and text features in

an incremental manner. We freeze the VI-ReID backbone and focus solely on fine-tuning the text encoder of the foundation model through end-to-end task-oriented training for aligning textual and fusion representations with all other modalities. This enables the text model to effectively learn complementary information from infrared features while maintaining the overall semantic stability of the text, thus creating fusion features more similar to visible features. Utilizing the powerful capability of text-visual alignment in foundation model, IFS incrementally fine-tunes LVM textual encoder to achieve text-visual alignment on expanded VI-ReID datasets, thereby seamlessly integrating complementary textual information into the existing VI-ReID framework to enrich infrared modality, effectively bridging the gap between infrared and visible modalities. Additionally, to maximize the utilization of semantically-rich query representations derived from the Incremental Fine-tuning Strategy, we introduce the Modality Ensemble Retrieving (MER) strategy. This approach averages features from the infrared, textual, and fusion modalities to create a robust composite query feature, enhancing retrieval accuracy. MER capitalizes on the unique strengths of each modality: infrared features provide continuous visual semantics; textual features offer descriptive information; fusion features ensure sharing the same semantic structure with visible features. This strategy fully utilizes information from all modalities, improves the robustness and accuracy of the retrieval.

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 text, reducing the cost of text annotations and enhancing the performance of cross-modality retrieval.
- We develop novel modules including Modal-Specific Caption (MSC), Incremental Fine-tuning Strategy (IFS) and Modality Ensemble Retrieving (MER), utilizing off-the-shelf foundation models to seamlessly empower the performance of the existing VI-ReID framework from data, optimization and inference level
- Extensive experiments demonstrate that our method significantly improves retrieval performance on three expanded cross-modality re-identification datasets, paving the way for applying foundation models in downstream cross-modality 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 faces significant modality gaps cased by limited information in IR images. Previous works [39, 4, 40, 19, 37] attempt to bridge this gap by mining shared discriminative information, but the absence of information in IR images hampers performance. [8] introduces manually designed coarse descriptions and relies on costly metric learning and independent modules for auxiliary information integration. It neglects the semantic connection between auxiliary information and vision, depends heavily on prior knowledge and is sensitive to variations in auxiliary data. In contrast, our framework can automatically generate diverse textual descriptions to enhance infrared data. By integrating a text encoder capable of text-visual alignment with existing VI-ReID backbone, and incrementally fine-tuning the textual encoder using classic ReID loss, this approach seamlessly enhances existing VI-ReID backbone without the need for additional complex implementations, with better robustness against variations in auxiliary data.

2.2 Foundation Model

Foundation models, pre-trained on extensive and diverse datasets[2], have shown great potential across various domains. Recent advancements in Language-Vision Models (LVMs) like GIT[32], BLIP[18], and CLIP[25], alongside Large Language Models (LLMs) such as GPT-2[26], GPT-3[3], Vicuna[44], and LLaMa2[29], have demonstrated remarkable data generation and semantic understanding capabilities. For instance, BLIP[18] excels at generating relevant textual descriptions from images, which can be fine-tuned on diverse image styles, thus can handle different visual modalities. Vicuna[44], a leading LLM, leverages its extensive pre-training on textual data for sophisticated text manipulation without losing semantic integrity, ideal for personalized text enhancements. Similarly, CLIP[25]'s pre-training on large-scale image-text pairs has enabled its ability to align text-image modalities and embed features into the same semantic space, streamlining modality alignment. Building on these capabilities, our approach integrates generative LVMs and LLMs for automatic textual data generation and augmentation. We also incorporate a text encoder pre-trained on vision-language pairs into the traditional VI-ReID system, enhancing cross-modality performance with textual information.

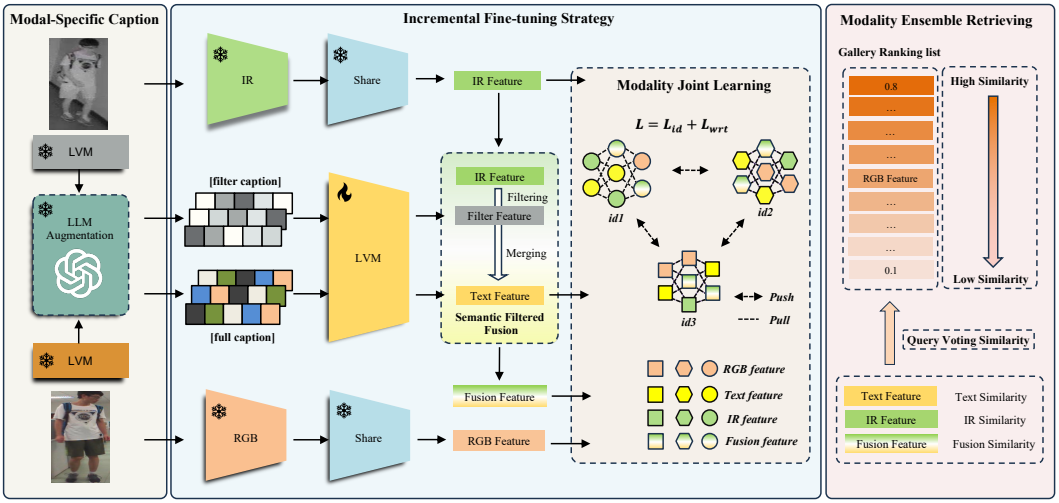


Figure 2: Illustration of TVI-FM: text-enhanced VI-ReID framework integrating a pre-trained LVM textual encoder[25] with a well-trained dual-stream visual backbone[12, 38].

3 Proposed Method

Task Setting. We utilize generated descriptions to enrich query representations for retrieval. Closely aligning with real-world application scenarios where witnesses provide varied descriptions to enhance query images for identifying individuals, each query q consists of an infrared sample V_i from the query set of original cross-modal datasets and a randomly selected textual description T_t generated from visible images for the same person, combining as $q = \{V_i, T_t\}$, while the gallery is composed by visible samples V_r. Then, we extract query and gallery representations through the model and compute ranking lists based on each query representation and all gallery representations as the retrieval results. Unlike traditional methods that solely utilize infrared queries, this query mode compensates for the infrared modality by integrating auxiliary information from descriptive sentences, having potential to enhance retrieval accuracy and robustness.

Overview. Our TVI-FM system, as depicted in Fig. 2, contains three parts. Modal-Specific Caption (MSC) employs LVMs to generate textual descriptions from visible and infrared images, subsequently utilizing LLM-based random rephrasing for their augmentation, thus creating diverse descriptions from cross-modal datasets without manual annotation efforts. Following this, the Incremental Fine-tuning Strategy (IFS) leverages the foundation model's intrinsic text-visual alignment capabilities to fine-tune the textual encoder on expanded datasets with representations of all modalities, seamlessly integrating complementary information from filtered textual features into the infrared modality to get fusion modality sharing the same semantic structure with visible modality. This effectively bridges the gap between infrared and visible modalities. To fully utilize all modalities' information, Modality Ensemble Retrieving (MER) aggregates features from all query modalities, thereby leveraging the combined strengths of each modality to improve retrieval accuracy and robustness.

3.1 Modal-Specific Caption

The Modal-Specific Caption (MSC) aims to automate the generation of high quality auxiliary descriptions for both infrared and visible images. It utilizes fine-tuned LVMs to generate text data from cross-modal datasets, then employs a Large Language Model (LLM) for textual augmentation, consequently creating diverse descriptions for visible and infrared images. This module reduces manual annotations and increases the system's robustness against auxiliary text variations.

LVM based Textual Generation. Due to the scarcity of large-scale Text-Visible-Infrared person re-identification datasets, we utilize Language Vision Models (LVMs) to generate textual descriptions for both visible and infrared images. Initially, we pre-train a Blip model on a vast pedestrian image-text dataset. We then randomly select visible-infrared image pairs from the SYSU-MM01's[34] training split and use this model to generate descriptions for visible images. After removing color-specific terms of the generated descriptions, we pair these adapted texts with corresponding infrared images in the same pairs to form an infrared-text sub-dataset. This sub-dataset was used to fine-

tune the Blip model, creating an infrared-specific captioner. This process enabled the autonomous generation of textual descriptions for datasets containing both modalities, eliminating the need for manual annotation. Through this method, we successfully constructed three cross-modal datasets: Tri-SYSU-MM01, Tri-LLCM, and Tri-RegDB. Further details are available in Appendix A.

LLM based Textual Augmentation. To ensure our framework extracting robust representations from generated textual descriptions against data variations, while preserving semantic integrity to enhance VI-ReID model, we implement an augmentation module based on LLM. This module regenerates more diverse descriptions for the same target, forcing the encoder to extract features with core semantics of person appearance. In detail, given an original description T, the module employs 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:

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

where $p = 0.5$ reflects the assumption that each description variant is equally probable. Utilizing the powerful prompt-driven text generation capability of LLM, this approach diversifies the textual descriptions while maintaining their core meanings. This forces the model to focus on extracting the core semantic of person appearance, thus enhancing the robustness of our system against text variation. Moreover, we can also apply this augmentation method directly on existing framework related with text data, without any change of the original structure.

3.2 Incremental Fine-tuning Strategy

The Incremental Fine-tuning Strategy (IFS) leverages the intrinsic capability of text-visual alignment contained in foundation models, aiming to integrate the complementary information of generated text into infrared modalities through incrementally tuning the textual encoder of LVM[25], thereby mitigating the gap between infrared and visible modalities. In detail, Semantic Filtered Fusion (SFF) refines textual features with filter features generated from infrared images, primarily creating enriched infrared features that share the same semantic structure as visible features. Modality Joint Learning (MJL) then optimizes the global association by aligning representations from all modalities, maximizing the effectiveness of information fusion in capturing complementary information for the infrared modality, while preserving the overall semantic stability of the text.

Semantic Filtered Fusion. Through LLM-based textual augmentation, the diverse textual descriptions can provide complementary information to infrared images. To leverage the intrinsic language-vision alignment capability for compensating infrared modality with complementary information from auxiliary textual descriptions, we introduce Semantic Filtered Fusion (SFF). First, we get features of infrared images by VI-ReID backbone and employ the textual encoder of a pre-trained LVM extract representations from descriptions generated for visible and infrared images. Moreover, leveraging the powerful text-visual capability, the textual encoder from the LVM maps textual features into a semantic space preliminarily aligned with vision, setting the stage for further refinement during the Modality Joint Learning (MJL) phase. Consequently, we can preliminarily form the fusion features jointly with text features and infrared features by summation and subtraction. However, while fusing the auxiliary information in text features f_t with infrared features f_i, they may contain redundant semantic details about the person's appearance, thus disrupting the semantic structural consistency with features from other modalities, so we selectively filter out redundant semantics in textual representations f_t that overlap with those found in infrared images by subtracting representations f_{filter} of descriptions generated for infrared images. Then we get the fusion features f_{sum} by composing the refined text features retaining rich complementary information with the infrared features:

$$f_{sum} = f_i + f_t - f_{filter} \tag{2}$$

This strategy leverages LVM's text-visual alignment capability to create fusion modalities. These preliminary fusion features composed of infrared feature and complementary information share the similar semantic structure with visible features, in following MJL, we refine the fusion modalities to further mitigate the difference between fusion features and visible features.

Modality Joint Learning. To further refine the fusion and textual features, thereby seamlessly integrating auxiliary information into existing VI-ReID frameworks, we propose Modality Joint Learning (MJL) for optimization. This strategy inherits the basic visual capabilities of the VI-ReID

system by freezing the backbone and focuses on incrementally fine-tuning the text encoder of the foundation model through end-to-end task-oriented training. This approach enables the text to align with vision and mine complementary information from text according to infrared modality. MJL optimizes the overall framework by adjusting the associations of representations from all modalities, including visible, infrared, textual, and fused modalities, using a task-oriented loss function. The total loss is composed of cross-entropy loss L_{id} and weighted regularized triplet loss L_{wrt}[39]:

$$L = L_{id} + L_{wrt} \tag{3}$$

Unlike other related works[8, 43, 5], leveraging the powerful intrinsic text-visual alignment capability of foundation models, MJL fine-tunes the whole framework with the classic ReID loss to integrate auxiliary textual information into infrared modalities and simultaneously mines discriminative information related to person identities, eliminating the need for manually designed processes or hyper-parameters. This strategy aligns representations across all modalities, enabling the text model to effectively learn complementary information according to infrared features while preserving the stability of the overall semantics of textual features. Consequently, it enhances infrared features to more closely resemble the visible modality, significantly bridging the gap between enriched infrared and visible modalities.

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 and robust retrieval, the Modality Ensemble Retrieving (MER) strategy is employed to comprehensively synthesize the unique and complementary advantages of different modalities. This involves averaging the features from the infrared modality f_i, textual modality f_t, and fusion modality f_{sum} to form a comprehensive query feature:

$$f_{agg} = mean(f_i, f_t, f_{sum}) \tag{4}$$

- ***Fusion features*** f_{sum} provide a comprehensive and enriched description of the target and aim to learn features with the same semantic structure as the visible modality, serving as the primary matching modality.
- ***Infrared features*** f_i provide valuable and contiguous visual semantics. Their similarity with visible images can serve as a supplementary reference for visual information.
- ***Textual features*** f_t provide descriptive details that may not be visually apparent or recognizable in infrared images. The similarity between textual features and visible features serves as an explicit reference for the missing or blurred appearance information in the infrared modality.
- ***The comprehensive features*** The retrieval results of f_{agg} and visible features f_r integrate the similarity scores of multiple query modalities with the visible modality to obtain a voting score, effectively harnessing the complementary strengths of each modality, reducing the potential impact of abnormal scores in sole-modal query-based retrieval lists through averaging with other modalities, and 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 cross-modal datasets with text description for each image are expanded from the original visible-infrared images datasets SYSU-MM01[34], RegDB[22], and LLCM[41] by the fine-tuned generative LVMs named Blip[18] in three stages (Details in Appendix A). The splits of the training set and testing set for each dataset are available in Appendix F.

Evaluation Protocols. In line with established VI-ReID settings [39, 37], we assess the performance of the infrared query mode and the textual enhanced infrared query mode using Rank-k matching accuracy, mean Average Precision (mAP), and mean Inverse Negative Penalty (mINP[39]) within our TVI-FM framework. To get stable performance on SYSU-MM01 and LLCM, we evaluate our model 10 times with random splits of the gallery set; as for RegDB, we evaluate our model on 10 trials with different training/testing splits. Finally, we report our model's average performance on each dataset.

Implementation Overview. We utilize a dual-stream ResNet-50[38] pretrained on ImageNet[27] as the visual backbone and a transformer in CLIP[25] as the textual encoder. Training involves visible and infrared images alongside text descriptions generated by two modality-specialized fine-tuned Blip[18] models, as detailed in Appendix A. All text descriptions are augmented by vicuna-7b[44]

Table 1: Ablation study on Text-enhanced Infrared query ($\boldsymbol{I + T \rightarrow R}$) 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	SFF	MJL	LLM	MER	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**

with a random rephrasing strategy. Incremental fine-tuning is applied by fixing the visual parameters and only tuning the textual part of the framework. All details are described in Appendix C.

4.2 Ablation Study

To thoroughly evaluate the effect of each component of our proposed method, we conduct comprehensive ablation studies on the Tri-LLCM and Tri-SYSU-MM01 datasets. These studies involve gradually adding the proposed modules to our baseline, systematically removing specific modules from our framework and assessing their impact on performance. The overall experimental setup remained consistent, with only the module under evaluation being modified.

Effect of Semantic Filtered Fusion. In order to form fusion queries sharing the same semantic structure with the visible modality, we implement a feature-level filtering mechanism utilizing LVM-generated filter features from IR images to compensate infrared features with filtered textual features. Compared with the baseline, the filter module enhances the framework's ability to comprehend the complementary semantics from text, while the baseline cannot effectively extract sufficient features from text. The method obtains a 4.48% Rank-1 improvement in Tri-SYSU-MM01 and a 1.90% Rank-1 improvement in Tri-LLCM, as shown in Table 1.

Effect of Modality Joint Learning. Incorporating SFF, and to further integrate auxiliary textual information into existing VI-ReID backbones, we propose Modality Joint Learning (MJL) to optimize the whole framework by aligning representations from all modalities. Based on the experimental results in Table 1, compared to the baseline only with filter mechanisms, adding this method gains a significant enhancement of 6.97% Rank-1 improvement, 6.67% mAP improvement, and 7.96% mINP improvement in Tri-SYSU-MM01, and 2.03% Rank-1 improvement, 2.63% mAP improvement, and 2.71% mINP improvement in Tri-LLCM.

Effect of Modality Ensemble Retrieving. The Modality Ensemble Retrieving strategy synthesizes the unique advantages of all query modalities, minimizing the potential impact of abnormal scores from single-modal queries 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. This demonstrates that the aggregation of different query modalities leads to more accurate and robust overall performance.

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

Discussion of Freezing Operation in IFS To seamlessly enhance the existing VI-ReID system with foundation models, we choose to fine-tune the textual LVM encoder and freeze the parameters of the existing VI-ReID model to inherit its capability of processing visual information and apply textual enhancement based on it. When we allow the visual backbone to update its parameters, as shown in the table from Appendix B, the performance of the integrated VI-ReID backbone suddenly declines by 5.43% and 4.24% in Rank-1 in the two datasets respectively. The performance of our

Table 2: 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 [33]	ICCV-17	$I \rightarrow R$	14.80	15.95	-	20.58	26.92	-
HCML [36]	AAAI-18		14.32	16.16	-	24.52	30.08	-
cmGAN [6]	IJCAI-18		26.97	27.80	-	31.63	42.19	-
AlignGAN [31]	ICCV-19		42.40	40.70	-	45.90	54.30	-
AGW [39]	TPAMI-21		47.50	47.65	35.30	54.17	62.97	59.23
DDAG [38]	ECCV-20		54.75	53.02	39.62	61.02	67.98	62.61
CM-NAS [11]	ICCV-21		61.99	60.02	-	67.01	72.95	-
DART [35]	CVPR-22		68.7	66.3	-	82.0	73.8	-
CAJ [37]	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 [41]	CVPR-23		74.70	71.80	-	80.30	83.30	-
SAAI [9]	ICCV-23		75.90	77.03	-	83.20	88.01	-
MSCLNet [40]	ECCV-22		76.99	71.64	-	78.49	81.17	-
SGIEL [10]	CVPR-23		77.12	72.33	-	82.07	82.95	-
PartMix [15]	CVPR-23		77.78	74.62	-	81.52	84.38	-
YYDS[8]	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 3: 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 [38]	ECCV-20	$I \rightarrow R$	68.06	61.80	48.62	40.3	48.4	-
AGW [39]	TPAMI-21		70.49	65.90	51.24	43.6	51.8	-
CAJ [37]	ICCV-21		84.8	77.8	61.56	48.8	56.6	-
DART [35]	CVPR-22		82.0	73.8	-	52.2	59.8	-
MMN [42]	MM-21		87.5	80.5	-	52.5	58.9	-
DEEN [41]	CVPR-23		89.5	83.4	-	54.9	62.9	-
YYDS[8]	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**

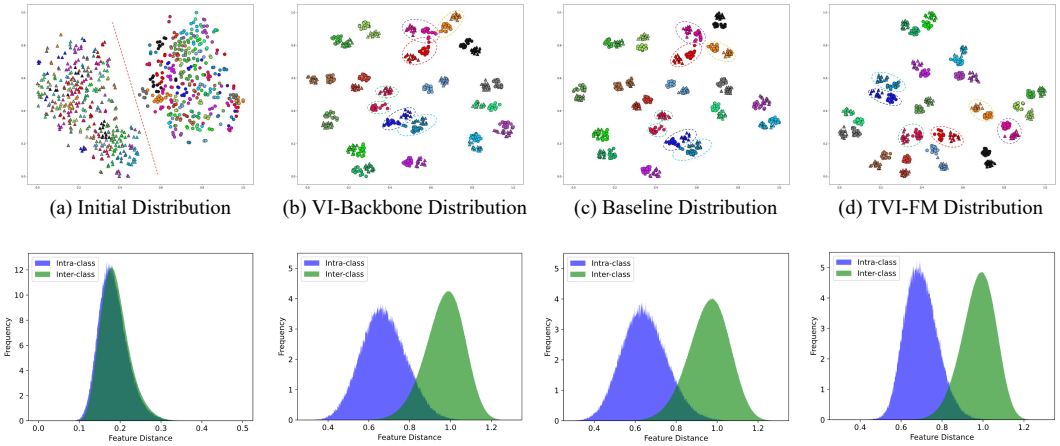
textually enhanced framework ($I + T \rightarrow R$) is also affected, with a decline of 0.14% Rank-1 in Tri-SYSU-MM01 and 1.66% Rank-1 in Tri-LLCM. This demonstrates the importance of freezing the integrated backbone to avoid the potential performance influence caused by conflicts of infrared feature learning and fusion feature learning during training.

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

In this section, we present comprehensive comparison of the proposed TVI-FM against state-of-the-art models on different datasets as outlined in Table 2 and Table 3. Our evaluation includes a variety of metrics: Rank-1 (R-1), mean Average Precision (mAP), and mean Inverse Negative Penalty (mINP). For fair comparison, we re-run YYDS on our proposed Tri-modal datasets with the same image size: 288×144.

Performance on Tri-SYSU-MM01 Dataset As shown in Table 2, with the enhancement of generated text, TVI-FM greatly improves the performance of the VI-ReID backbone and outperforms all previous methods under 'All Search' and 'Indoor Search' conditions. Specifically, TVI-FM achieves significant improvements 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 are substantial increases from the previous high scores of 77.03% and 88.01%, respectively.

Performance on Tri-RegDB and Tri-LLCM Dataset Table 3 outlines our method's performance on the two datasets. In the Tri-RegDB dataset, TVI-FM obtains a Rank-1 of 91.38% and an 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



(a) Initial Distribution (b) VI-Backbone Distribution (c) Baseline Distribution (d) TVI-FM Distribution

(e) Initial Distance (f) VI-Backbone Distance (g) Baseline Distance (h) TVI-FM Distance

Figure 3: First row (a-d) show the t-SNE feature distribution of the 20 randomly selected identities, triangle means infrared features(w/wo textual enhancement), 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.

Tri-LLCM dataset, our method leads with a Rank-1 of 58.19% and an 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[30] 2D feature space and visualize cosine distances of the intra-class and inter-class features on Tri-SYSU-MM01 dataset in Fig. 3. From the 'Initial' to 'TVI-FM' in Fig. 3(a-d), the t-SNE feature distribution shows that our method greatly enhances the ability of distinguishing features from different identities with text and reduces extreme outliers of the same identity and samples with too large cross modal discrepancy. While for feature distance distribution in Fig. 3(e-h), corresponding to 2D t-SNE[30] feature distribution, the inter/intra-class distance distributions are increasingly separated well, especially, the 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 VI-ReID backbone, baseline and our method on the Tri-SYSU-MM01 dataset in Appendix E. For the same query image, our method significantly enhances retrieval performance utilizing generated descriptions compared to baseline and VI-ReID backbone.

5 Conclusion

This paper introduces a novel framework for text-enhanced Visible-Infrared Person Re-identification (VI-ReID) driven by Foundation Models (TVI-FM). Traditional VI-ReID often struggles compared to RGB-based ReID due to significant modality differences, notably the absence of information of infrared modality. Our approach addresses this by enriching the infrared modality with automatically generated textual descriptions. We incorporate a pre-trained LVM to extract textual features from descriptions generated by fine-tuned LVMs and augmented by LLM. To enrich infrared features with generated text, we use modality alignment capabilities of LVMs and LVM-Generated feature-level Filters to create preliminary fusion modality. This enables text model to learn complementary information according to infrared modality, ensuring semantic consistency between the fusion and visible modalities. Then, modality joint learning aligns features of all modalities by fine-tuning the text model to adapt to the frozen VI-ReID backbone, maintaining the stability of the overall semantics of text representations while refining text-enriched infrared representations, thus minimizing the domain gap between enriched infrared and visible modalities. Additionally, the Modality Ensemble Retrieving strategy enhances retrieval performance by leveraging the strengths of each query modality. Extensive experiments on three expanded cross-modal datasets demonstrate significant improvement in retrieval performance, paving the way for applying 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[8] 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 fine-tune LVMs to generate textual descriptions for both visible and infrared images, thereby constructing three large scale tri-modality datasets: Tri-SYSU-MM01, Tri-LLCM and Tri-RegDB from the original datasets SYSU-MM01[34], LLCM[41], RegDB[22] separately. The details are introduced in following steps below:

1) *Getting the LVM ables to Generate Textual description from RGB images*: We pre-train Blip[18] on a large-scale pedestrian image-text dataset [28] to get the captioner for visible images.

2) *Getting the LVM able to Generate Textual description from IR images*: Firstly randomly select visible and infrared images pairs in SYSU-MM01's training split for every identity, then apply the captioner we got in **step 1** to generate textual descriptions for every visible images in these pairs. Then we remove color-related terms from these generated text by regular expression filter, build Infrared-Text(filtered) pairs dataset with filtered text descriptions and corresponding infrared images in the same expanded visible-infrared pairs. Finally we fine-tune the Blip[18] got from **step 1** on the IR-Text(filtered) dataset, get the captioner for infrared 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 4. And the visualization on samples of our datasets are shown in 4. All the fine-tuning process of LVMs are from documentations from huggingface `https://huggingface.co/docs/transformers/main/en/tasks/image_captioning`, the generator model we use refers to `https://huggingface.co/Salesforce/blip-image-captioning-large`.

Table 4: 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

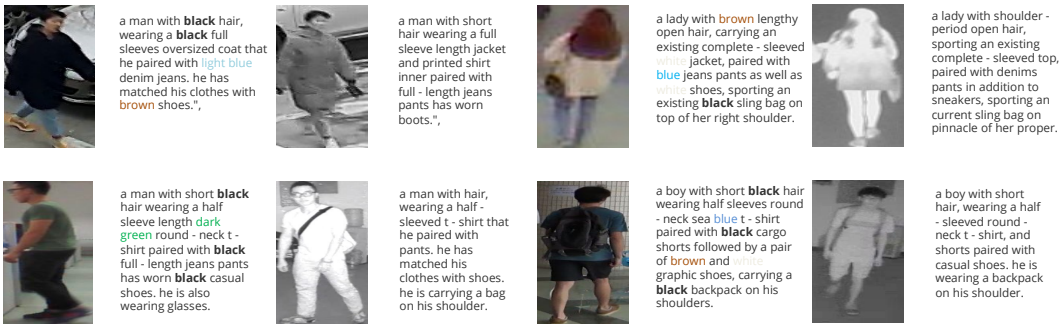

Figure 4: Visualization of the data samples selected from the expanded three datasets.

B Ablation Study of Freezing Operation in IFS

Table 5: The influence of whether to freeze visual backbone on case of infrared query ($\boldsymbol{I} \rightarrow \boldsymbol{R}$) and text-enhanced 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 **MER** 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**

C Implementation Details

We implement our framework in PyTorch [23] 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 [37]. All text descriptions are generated by two modality-specialized fine-tuned LVMs and augmented by the proposed LLM rephrasing augmentation with a probability of 0.5, here we use vicuna-7b [44] as our LLM model, use Blip[18] as our LVM model, whose tuning process can be found in AppendixA. We employ a dual-stream resnet50 model [38] pre-trained on ImageNet [27] as the visual backbone and a transformer model with parameters derived from CLIP [25] 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 [37] 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[21] applied for each feature for 20 epochs. We use the Adam[14] 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.

D 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.

E Retrieve Result Examples w/wo Text

Figure 5: Visualization of the rank-5 retrieval results obtained by the VI-ReID backbone on the proposed Tri-SYSU-MM01.

The VI-ReID backbone and baseline still includes misidentifications. But our method optimally leverages rich complementary information from textual data, significantly enhancing retrieval performance through modality fusion at a semantic level. It can be found that even the hard query samples that fail to retrieve correct targets still exhibit high appearance semantic similarity with the target identity.

F Assets Details

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

- **SYSU-MM01**[34]
  - *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**[41]
  - *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**[22]
  - *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`
  - *License*: CC-BY 4.0

G 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)Improving room still exists in handling challenging datasets such as LLCM[41]. 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.

NeurIPS Paper Checklist

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   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

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   Justification: We demonstrate clearly our main claim that leveraging foundation models to generate enhanced and encoded textual modalities effectively addresses the challenges faced in VI-ReID and enhances retrieval performance. Our experimental results show significant improvements on retrieval accuracy across all three proposed datasets.

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