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Dual Prompt-Driven Feature Encoding for Nighttime UAV Tracking

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***Abstract*— Robust feature encoding constitutes the foundation of UAV tracking by enabling the nuanced perception of target appearance and motion, thereby playing a pivotal role in ensuring reliable tracking. However, existing feature encoding methods often overlook critical illumination and viewpoint cues, which are essential for robust perception under challenging nighttime conditions, leading to degraded tracking performance. To overcome the above limitation, this work proposes a dual prompt-driven feature encoding method that integrates prompt-conditioned feature adaptation and context-aware prompt evolution to promote domain-invariant feature encoding. Specifically, the pyramid illumination prompter is proposed to extract multi-scale frequency-aware illumination prompts. The dynamic viewpoint prompter modulates deformable convolution offsets to accommodate viewpoint variations, enabling the tracker to learn view-invariant features. Extensive experiments validate the effectiveness of the proposed dual prompt-driven tracker (DPTracker) in tackling nighttime UAV tracking. Ablation studies highlight the contribution of each component in DPTracker. Real-world tests under diverse nighttime UAV tracking scenarios further demonstrate the robustness and practical utility. The code and demo videos are available at https://github.com/yiheng-wang-duke/DPTracker.**

I. Introduction

Unmanned aerial vehicle (UAV) tracking has seen widespread adoption in applications, *e.g.*, localization and landing [1], traffic surveillance [2], and autonomous navigation [3]. With the advancement of deep neural networks and the availability of large-scale annotated datasets, UAV tracking has achieved remarkable performance gains. A key component contributing to these advances is strong feature encoding ability of deeper models, which enables the construction of discriminative representations by capturing both appearance and motion cues, thereby forming the basis for accurate target localization and trajectory estimation. However, when applied to nighttime scenarios, UAV tracking remains highly challenging due to severe illumination degradation and low contrast in low-light imagery, as well as the UAV platform's unique aerial viewpoints. The limited consideration of illumination and viewpoint cues in feature encoding of state-of-the-art (SOTA) trackers undermines reliable feature extraction, leading to poor performance in nighttime UAV tracking scenarios [4], [5]. Addressing the feature encoding insufficiency is critical for enabling reliable and extensive UAV applications.

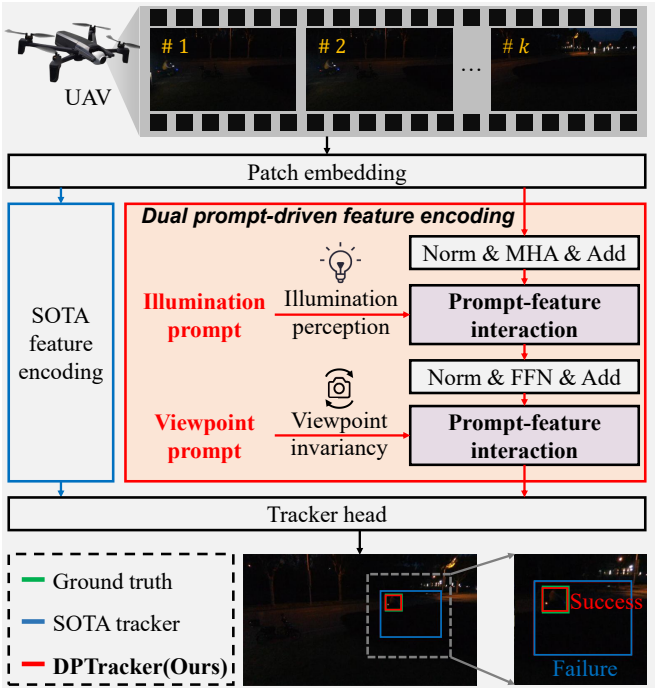

Fig. 1. The overall comparison between the SOTA method and the proposed DPTracker. With prompt-feature interaction, DPTracker learns adaptive features and outperforms SOTA trackers in nighttime UAV tracking.

Building on recent advances in deep learning, many SOTA trackers adopt Vision Transformer [6] (ViT) architectures due to the strong capability in modeling global dependencies and spatial relations. A typical ViT-based tracking paradigm follows a three-stage pipeline: patch embedding, feature encoding, and prediction head. Specifically, the input image is first divided into non-overlapping patches, which are then linearly projected into patch embeddings. The embeddings are processed by a stack of ViT blocks to extract high-level features. Finally, a tracker head decodes these features to predict the target's location and bounding box. However, the SOTA trackers are not sufficiently effective for nighttime UAV tracking because their feature encoding lacks robustness to domain-specific challenges [4]. Under low-light conditions and dynamically varying aerial viewpoints, the encoded visual tokens often suffer from degraded quality, misaligned positional cues, and distorted semantic consistency, which collectively lead to biased query–key relationships and unreliable attention formation. Therefore, ***it is essential to incorporate illumination and viewpoint information into the feature encoding stage to ensure reliable representations for robust nighttime UAV tracking***.

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To address the problem, this work proposes the dual prompt-driven feature encoding block (DPBlock) to integrate illumination and viewpoint prompt semantics into the feature encoding of the ViT backbone. DPBlock establishes prompt-conditioned guidance, where the generated prompt tokens modulate features, enabling the model to attend to critical visual cues under degraded conditions. The prompt-driven feature encoding enhances the model's capacity to adapt representation to low-light environments and dynamic aerial viewpoints, thereby improving robustness in nighttime UAV tracking scenarios. In parallel, intermediate representations are leveraged to refine the prompt tokens through feedback connections, enabling the prompt tokens to dynamically adjust based on the evolving feature context and better inform subsequent conditioning.

This work further designs prompters to learn prompt tokens that capture illumination information and encode the dynamic aerial viewpoint characteristics, as shown in Fig. 1. The pyramid illumination prompter, inspired by the Laplacian pyramid [7], is designed to hierarchically extract multi-scale illumination features from the input image. By approximating the Laplacian decomposition structure, the prompter captures frequency-aware features, which are then aggregated into illumination prompt tokens that effectively represent the illumination conditions. In addition, a dynamic viewpoint prompter is developed to extract viewpoint information for prompt-driven feature encoding. This module leverages deformable convolution to learn adaptive offsets for feature sampling, enabling the viewpoint prompt tokens to perceive geometric variations arising from dynamic UAV viewpoints, thereby enhancing tracker adaptation to diverse aerial viewpoints and camera poses. The contributions of this paper are summarized as:

- An innovative dual prompt-driven feature encoding method is proposed, which integrates the prompt-feature interaction mechanism into the ViT backbone, enabling explicit bidirectional adaptation between prompt tokens and visual features for illumination-aware and viewpoint-invariant representation learning.
- A novel pyramid illumination prompter is designed to approximate the Laplacian pyramid, hierarchically generate multi-scale illumination features, and further aggregate them into the illumination prompt tokens.
- A dynamic viewpoint prompter is proposed to generate viewpoint prompt tokens, utilizing deformable convolution to adapt spatial sampling to different viewpoints.
- Extensive experiments on nighttime UAV tracking benchmarks demonstrate the effectiveness of DP-Tracker, while real-world tests further validate its applicability and superior performance in practical scenarios.

II. Related Work

A. Nighttime UAV Tracking

Recent nighttime UAV tracking research is categorized into four paradigms: low-light image enhancement, domain adaptation, training from scratch, and prompt tuning. Low-light enhancement approaches [8] employ plug-and-play modules to brighten images before tracking. While boosting visual quality, such preprocessing is loosely coupled with feature encoding and often yields suboptimal representations for tracking. Domain adaptation methods aim to bridge the distribution gap between daytime and nighttime images in an unsupervised manner. UDAT [4] pioneers this approach by employing adversarial training to learn domain-invariant features. SAM-DA [9] improves sample quality through SAM-based swelling. TDA [10] incorporates temporal context adaptation into the domain adaptation framework. However, without explicitly modeling illumination and viewpoint cues, unsupervised domain adaptation methods often suffer from training instability and limited robustness. Training-from-scratch methods directly train models using nighttime object detection annotations. DARTer [11] exploits multi-perspective features and dynamic feature activators to achieve better tracking performance, while MambaNUT [12] employs Vision Mamba architectures with tailored data sampling and loss scheduler. Nevertheless, training-from-scratch approaches are time-consuming and prone to overfitting due to limited nighttime training data, making the learned feature encoding less generalizable. Prompt tuning offers a training-efficient and well-performing alternative solution by injecting task-related priors into the feature encoding. However, the feature encoding of existing prompt-based trackers insufficiently incorporates illumination and viewpoint information, which in turn restricts their robustness under challenging nighttime UAV tracking conditions.

B. Prompt Tuning for Tracking

Prompt tuning methods have emerged as an effective paradigm for adapting frozen pre-trained foundation models to various tracking scenarios with minimal parameter overhead. ViPT [13] and OneTracker [14] introduce modality-relevant visual prompts to bridge the domain gap in multi-modal tracking. UM-ODTrack [15] further incorporates dense temporal token association and gated modules for adaptive cross-modal representation learning. MM-Track [16] enhances the robustness of multi-modal representations by adaptively transferring discriminative cues while maintaining temporal consistency. MPT [17] proposes a lightweight motion prompt module that encodes long-term trajectory information into the visual embedding space. DCPT [18] pioneers the prompt tuning techniques in nighttime UAV tracking. It introduces a darkness clue prompter that injects anti-dark knowledge into a frozen daytime tracker. However, these prompt tuning methods for visual tracking fail to consider both illumination conditions and dynamic aerial viewpoint in feature encoding, resulting in insufficient feature representations for nighttime UAV tracking. Therefore, developing prompters to extract rich illumination and viewpoint semantics is necessary to advance prompt tuning-based nighttime UAV tracking.

III. Methodology

In this section, the proposed method is clearly illustrated. Section III-A introduces the dual prompt-driven feature en-

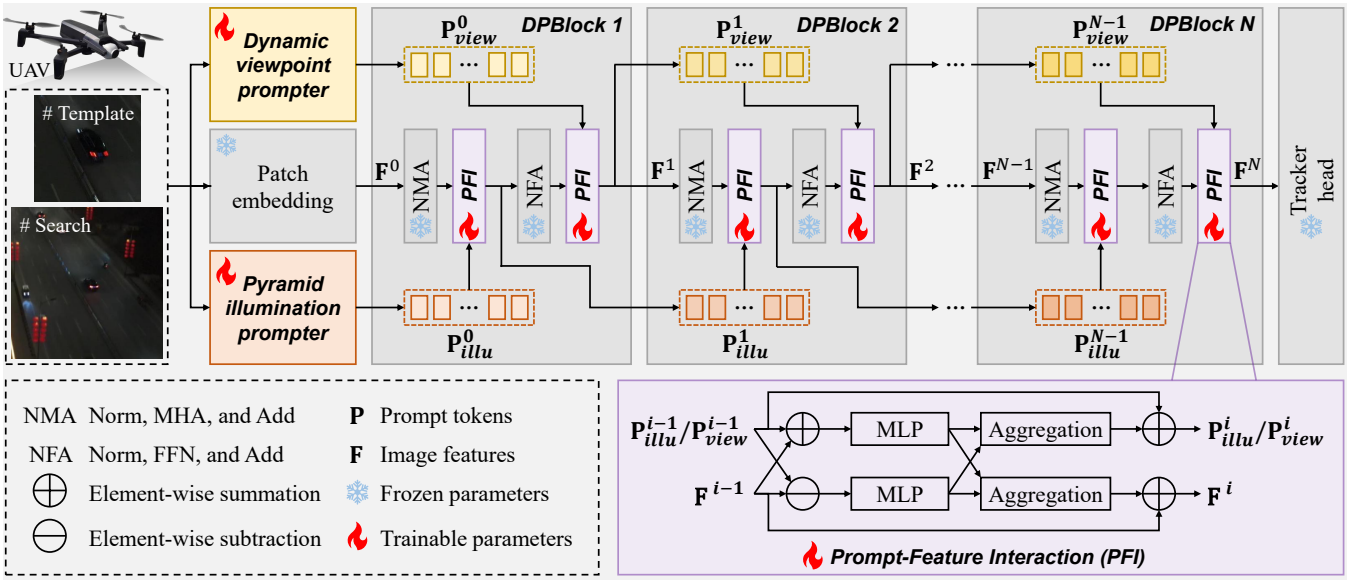


Fig. 2. Overall model architecture of DPTracker. The interaction between prompt tokens and features integrates prompt semantics into the features while updating the prompt tokens, thereby enhancing nighttime UAV tracking with more adaptive representations. The images are from NAT2021-*test* [4].

coding module, which enables prompt-conditioned feature adaptation and context-aware prompt evolution. Section III-B presents the pyramid illumination prompter, which extracts multi-scale, frequency-aware illumination prompt tokens. Section III-C describes the dynamic viewpoint prompter, which adaptively deforms convolutional kernels to capture viewpoint prompt tokens from UAV-view images.

A. Dual Prompt-Driven Feature Encoding

To empower feature encoding with illumination and viewpoint cues, this work proposes the dual prompt-driven feature encoding module (DPBlock). As shown in Fig. 2, DPBlock integrates two prompt-feature interaction (PFI) modules within the ViT structure. The first PFI module is integrated after the self-attention sub-layer of ViT to disambiguate target features from low-contrast backgrounds. By injecting illumination-aware semantics, it compensates for MHA's tendency to produce indistinguishable responses in poorly-lit environments. The second PFI module follows the feed-forward sub-layer to cultivate viewpoint-invariant representations. While FFN deepens per-token semantics, the PFI module rectifies the severe geometric distortions inherent in UAV tracking with dynamic viewpoints. Specifically, PFI is composed of two complementary methods, *i.e.*, prompt-conditioned feature adaptation and context-aware prompt evolution. Prompt-conditioned feature adaptation integrates semantic cues from the prompt tokens into the feature representations. Context-aware prompt evolution updates the prompt tokens with the latest feature context, enabling them to convey more precise guidance for feature adaptation.

The prompt-conditioned feature adaptation incorporates element-wise summation and subtraction to characterize the interplay between the prompt tokens $\mathbf{P}_k^i \in \mathbb{R}^{N\times d}$ and the features $\mathbf{F}^i \in \mathbb{R}^{N\times d}$, where i denotes the index of the DPBlock and $k \in \{illu, view\}$ indicates the type of prompt tokens. Specifically, the summation operation reinforces shared feature manifolds to model the similarity between the prompt and the latent representation, while the subtraction isolates residual, distinctive components to capture the discrepancies between them. Then, the multi-layer perceptron modules are applied to enhance and exaggerate the encoded semantic similarity and difference. The process is formulated as:

$$\mathbf{E}_{sim}^i = LN(MLP(\mathbf{F}^{i-1} + \mathbf{P}_k^{i-1})) \ , \tag{1}$$

$$\mathbf{E}_{dif}^i = LN(MLP(\mathbf{F}^{i-1} - \mathbf{P}_k^{i-1})) \ , \tag{2}$$

where $\mathbf{E}_{sim}^i$ and $\mathbf{E}_{dif}^i$ denote the similarity-aware features and the difference-aware features in the i-index DPBlock, MLP function as the multi-layer perceptron module, and LN denotes layer normalization.

The prompt-conditioned feature adaptation further incorporates the similarity cues and suppresses difference cues, ensuring that the feature representations emphasize semantic alignment with the prompt tokens. The adaptation utilizes a simple weighted aggregation strategy, formulated as:

$$\mathbf{F}^i = \mathbf{F}^{i-1} + \alpha_f \cdot \mathbf{E}_{sim}^i - \beta_f \cdot \mathbf{E}_{dif}^i \ , \tag{3}$$

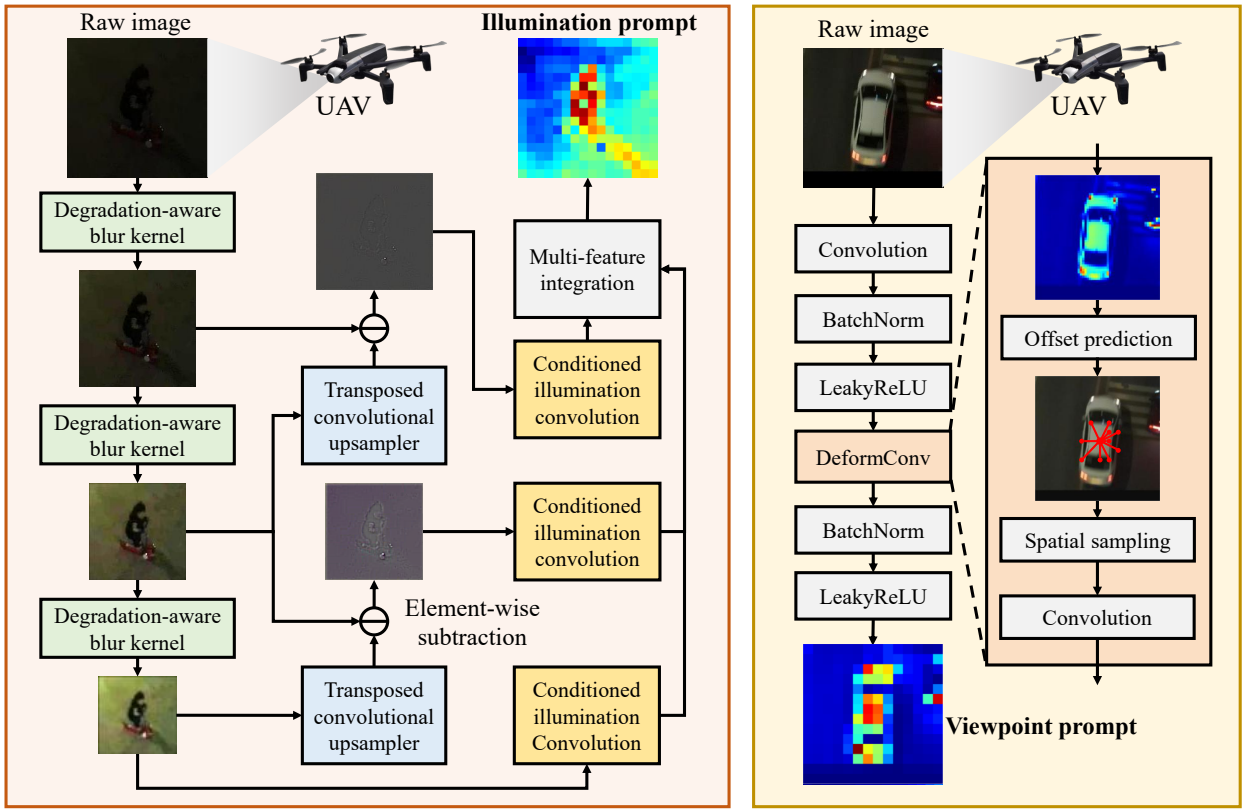
where α_f and β_f are learnable coefficients that determine the contribution of each component in the feature adaptation.

The context-aware prompt evolution leverages a similar but asymmetric weighted aggregation method. It attenuates similarity cues and enhances difference cues, enabling the prompt tokens to dynamically adapt to the latest feature context and provide more effective guidance for subsequent feature adaptation. The process is formulated as:

$$\mathbf{P}^i = \mathbf{P}^{i-1} - \alpha_p \cdot \mathbf{E}_{sim}^i + \beta_p \cdot \mathbf{E}_{dif}^i \ , \tag{4}$$

where α_p and β_p are learnable coefficients.

Remark 1: Dual prompt-driven feature encoding method achieves a dynamic interplay where features absorb semantic guidance from prompt tokens, while prompt tokens evolve based on the latest feature context to provide more precise adaptation guidance.



(a) Pyramid illumination prompter (b) Dynamic viewpoint prompter

Fig. 3. The architecture of the pyramid illumination prompter and the dynamic viewpoint prompter. The illumination prompter leverages a learnable pyramid network to decompose images and aggregate multi-scale features, while the dynamic viewpoint prompter combines standard and deformable convolutions to adaptively capture viewpoint information under UAV perspectives. The images are from DarkTrack2021 [8].

B. Pyramid Illumination Prompter

To learn nighttime adaptive features, the pyramid illumination prompter (PIP) is proposed to comprehensively encode the lighting conditions into the illumination prompt tokens. Previous research [19] has demonstrated that the low-frequency levels of the Laplacian pyramid encode substantial illumination and contrast-related information, while the mid-frequency and high-frequency levels of the Laplacian pyramid focus on structural information. Therefore, the Laplacian pyramid is particularly well-suited for learning the illumination prompt. Building upon this insight, the PIP is designed with a hierarchical architecture to approximate the Laplacian pyramid structure, as shown in Fig. 3. The traditional non-learnable operators for constructing the Laplacian pyramid are replaced by learnable convolutional components to improve the prompt learning capabilities.

Given a raw image $\mathbf{I}$, the PIP employs degradation-aware blur kernels whose weights are initialized to approximate Gaussian blur kernels, which preserves the hand-crafted prior knowledge and allows the model to adaptively refine features. The PIP constructs a multi-scale feature hierarchy inspired by the Gaussian pyramid, formulated as:

$$\mathbf{G}_0 = \mathbf{I} \ , \quad \mathbf{G}_{i+1} = DBK(\mathbf{G}_i) \ , \tag{5}$$

where $DBK(\cdot)$ denotes the learnable degradation-aware blur kernel at level i, and $\mathbf{G}_i$ denotes the blurred image.

Traditional upsampling operations are replaced with transposed convolutional upsamplers, which allow the model to learn richer and more informative representations of illumination at each scale. Residual connections are introduced by subtracting the upsampled lower-frequency features from the corresponding higher-frequency features, approximating the Laplacian response at each scale. The whole process is formulated as:

$$\mathbf{L}_i = \mathbf{G}_i - UP_i(\mathbf{G}_{i+1}) \ , \tag{6}$$

where $UP_i(\cdot)$ denotes the transposed convolutional upsampler at level i and $\mathbf{L}_i$ denotes the corresponding Laplacian component at level i.

The conditioned illumination convolutional layers are applied to each Laplacian component, and the final illumination prompt $\mathbf{P}_{illu}$ is generated by concatenating the responses from all levels along the channel dimension:

$$\mathbf{P}^0_{illu} = \mathrm{Concat}(Conv_0(\mathbf{L}_0), \ldots, Conv_n(\mathbf{L}_n)) \ , \tag{7}$$

where $\mathrm{Concat}(\cdot)$ denotes the channel-wise concatenation and n is the total number of scales.

Remark 2: By emulating the Laplacian pyramid in a learnable and differentiable manner, the PIP effectively captures multi-scale illumination information. The illumination prompt tokens are essential for adapting representations to various illumination conditions in nighttime UAV tracking scenarios.

C. Dynamic Viewpoint Prompter

Nighttime UAV tracking suffers from significant geometric and semantic variations due to the inherently dynamic nature of aerial viewpoints. To address this issue, a viewpoint prompter capable of dynamically capturing geometric information is introduced, thereby facilitating feature adaptation to the dynamic viewpoints of nighttime UAV tracking.

As shown in Fig. 3, the dynamic viewpoint prompter (DVP) is designed to learn viewpoint prompt tokens through a coarse-to-fine prompt generation strategy. Initially, DVP employs a standard convolutional layer to extract local features from small image patches, capturing spatial structures that serve as coarse viewpoint prompt tokens of the scene. Given an input image $\mathbf{I}$, the coarse viewpoint prompt tokens are computed as:

$$\mathbf{P}^{c}_{view} = LR(BN(Conv(\mathbf{I}))) \ , \tag{8}$$

where $\mathbf{P}^{c}_{view}$ denotes the coarse viewpoint prompt tokens, BN represents the batch normalization, and LR denotes the LeakyReLU activation function.

DVP subsequently applies a deformable convolutional layer to further enhance finer viewpoint adaptivity. Unlike standard convolutions with fixed grid-based sampling, deformable convolutions introduce learnable spatial offsets, enabling each kernel position to adaptively sample from geometrically relevant regions. The offset field $\Delta P \in \mathbb{R}^{2K\times H\times W}$, where K is the number of sampling points, is predicted from the coarse viewpoint prompt tokens $\mathbf{P}^{c}_{view}$ by an offset generation module, which is formulated as:

$$\Delta P = OffConv(\mathbf{P}^{c}_{view}) \ , \tag{9}$$

$$\Delta P = \{\Delta p_1, \Delta p_2, \ldots, \Delta p_K\} \ , \tag{10}$$

where ΔP is the predicted offset and $OffConv$ is the offset convolutional layer. Each $\Delta p_i \in \mathbb{R}^2$ denotes the offset for the i-th sampling position.

The deformable convolution at position p_0 is computed as:

$$\mathbf{R}(p_0) = \sum_{k=1}^{K} w_k \cdot \mathbf{P}^{c}_{view}\big(p_0 + p_k + \Delta p_k\big) \ , \tag{11}$$

where p_0 is the reference spatial location on the feature map, p_k denotes the predefined sampling location in the regular convolution kernel, w_k denotes the learnable kernel weight for the k-th sampling location, and $\mathbf{R}(p_0)$ is the output feature at location p_0.

DVP further applies batch normalization and LeakyReLU activation to generate the final fine-grained viewpoint prompt tokens, which is formulated as:

$$\mathbf{P}^{0}_{view} = LR(BN(\mathbf{R})) \ , \tag{12}$$

where $\mathbf{P}^{0}_{view}$ denotes the viewpoint prompt tokens.

Remark 3: DVP produces viewpoint prompt tokens that encapsulate rich geometric and semantic cues through coarse-to-fine refinement. The viewpoint prompt tokens provide vital adaptive guidance for feature learning under challenging nighttime UAV viewpoints.

IV. Experiments

A. Implementation Details

The models developed upon existing SOTA general object tracking models AVTrack [5] and OSTrack [20] baselines are denoted as DPTracker-T and DPTracker-B, respectively. A mixture of daytime and nighttime object tracking data are used for training. The daytime training data include GOT-10K [29], LASOT [30], COCO [31], and TrackingNet [32], while the nighttime training datasets include ExDark [33], Shift [34], and BDD100K [35]. The models are trained with classification and regression losses for 30 epochs using the AdamW [36] optimizer on 2 NVIDIA A100 GPUs. The initial learning rate is set to 0.0004, which decays at a rate of 10% at 24 epochs.

B. Overall Performance Evaluation

As shown in Table I, experiments are conducted to comprehensively evaluate the proposed method against SOTA trackers on three benchmarks [4], [8], [22]. The bounding box in the first frame of each sequence is provided.

UAVDark135 [22] is a widely recognized benchmark designed for evaluating object tracking performance in low-light UAV scenarios. Compared with SOTA trackers of similar model size, DPTracker-T achieves the best overall performance across all three metrics, with precision of **56.8%**, normalized precision of **51.8%**, and success rate of **45.6%**, surpassing other SOTA lightweight tracking methods. As tracker size increases, DPTracker-B establishes new state-of-the-art results with precision of **72.3%**, normalized precision of **65.2%**, and success of **58.1%**. Compared to the SOTA method [18], DPTracker-B improves by **+2.0%**, **+1.3%**, and **+1.0%** in three metrics respectively, demonstrating notable gains in both robustness and accuracy. As shown in Fig. 4, the visualization results indicate the superior capability of DPTracker-B in nighttime UAV tracking.

DarkTrack2021 [8] is an authoritative dataset comprising 110 sequences, widely adopted for evaluating UAV tracking under nighttime conditions. Compared with trackers of similar size, DPTracker-T achieves superior performance across all three evaluation metrics, reaching **59.1%** precision, **51.9%** normalized precision, and **46.5%** success rate, exceeding all competing tracking methods. When scaling to larger trackers, DPTracker-B outperforms other models with precision **69.8%**, normalized precision **62.2%**, and success rate **55.8%**. Compared to the SOTA tracker [18], DPTracker-B achieves a relative improvement of **+2.7%**, **+2.3%**, and **+2.1%** across the three metrics, underscoring its robustness and strong adaptability in nighttime UAV tracking.

NAT2021-*test* [4] is a large-scale benchmark containing 180 video sequences. When evaluated against trackers of similar scale, DPTracker-T achieves new state-of-the-art performance with precision of **65.4%**, normalized precision of **53.8%**, and success rate of **47.5%**. As the trackers scale up, DPTracker-B performs the best among all trackers with precision **73.9%**, normalized precision **62.5%**, and success rate **55.9%**. These consistent improvements confirm the

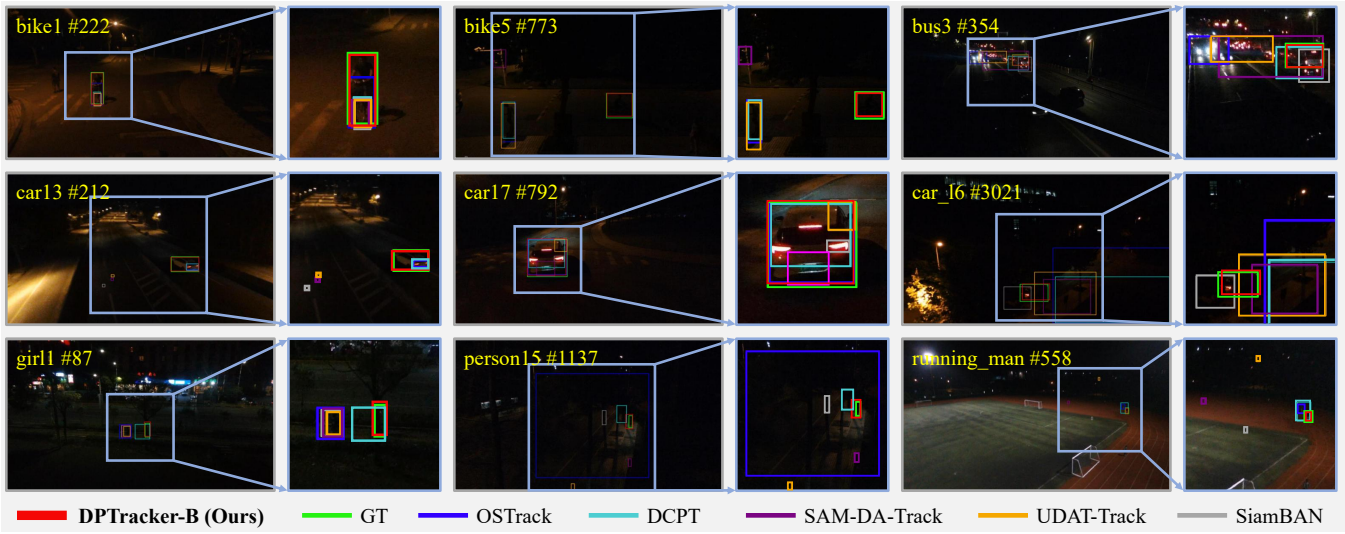


Fig. 4. Tracking result visualization of DPTracker-B along with other top trackers [4], [9], [18], [20], [21]. The sequences are selected from UAVDark135 [22]. The proposed DPTracker-B shows more robust and precise tracking performance under diverse nighttime UAV tracking scenarios.

effectiveness of the proposed method in nighttime UAV tracking across various challenging scenarios.

C. Attribute-Based Evaluation

To further investigate tracking robustness under diverse nighttime UAV tracking challenges, a further attribute-based evaluation, as shown in Fig. 5, is conducted across eight key factors: aspect ratio change (ARC), background clutter (BC), camera motion (CM), illumination variation (IV), low ambient intensity (LAI), partial occlusion (PO), similar object (SO), and viewpoint change (VC). DPTracker-T achieves the most robust performance among trackers with similar model scales, excelling under low ambient intensity **44.1%** and illumination variation **44.7%**. DPTracker-B also demonstrates remarkable superiority under illumination-related challenges, achieving the highest success rates in scenarios with low ambient intensity **51.3%** and illumination variation **52.9%**. Beyond illumination robustness, DPTracker also consistently outperforms other trackers across the remaining attributes with notable advantages. These results validate the effectiveness of the proposed approach in handling challenges in nighttime UAV tracking scenarios.

D. Ablation Study

To investigate the effectiveness of each component, ablation experiments are conducted on PFI, PIP, and DVP using two evaluation metrics: precision and success rate, as shown in Table II. To validate the PFI module in the prompt-driven feature encoding, the prompters are replaced with the patch embedding modules. Using PFI brings noticeable relative gains of +5.3% and +4.5% in the two metrics, demonstrating that PFI can effectively enhance the feature encoding for nighttime UAV tracking. PIP and DVP provide granular refinements to further calibrate and polish the learned representations. Utilizing PIP further achieves a performance of 71.9% and 57.8% on the two metrics, while incorporating DVP yields a performance of 72.3% and 58.1% on the two metrics. These results verify that PFI, PIP, and DVP jointly

TABLE I

COMPARISON OF TRACKING PERFORMANCE ON UAVDARK135 [22], DARKTRACK2021 [8], AND NAT2021-*test* [4] BENCHMARKS. THE PROPOSED DPTRACKER-B AND DPTRACKER-T OUTPERFORM OTHER TRACKERS BY NOTABLE MARGINS.

Method	**Source**	**UAV**	**UAVDark135 [22]**			**DarkTrack2021 [8]**			**NAT2021-*test* [4]**			**Params**
			Prec.	Norm.Prec.	Succ.	Prec.	Norm.Prec.	Succ.	Prec.	Norm.Prec.	Succ.	(M)
SiamAPN [23]	ICRA 21	✓	42.4	39.5	30.1	41.9	37.9	30.7	55.8	41.8	33.7	15.2
SiamAPN++ [24]	IROS 21	✓	42.3	39.1	32.5	48.3	43.5	36.5	60.8	48.4	40.8	15.4
TCTrack [25]	CVPR 22	✓	48.8	45.4	36.2	53.5	46.8	39.3	61.2	46.8	39.4	10.4
TCTrack++ [26]	TPAMI 23	✓	47.7	44.5	37.0	56.4	48.8	42.1	61.7	48.1	40.8	15.2
AVTrack-ViT [5]	ICML 24	✗	56.1	51.0	44.8	56.1	49.4	44.4	61.7	50.6	44.3	20.9
DPTracker-T	**Ours**	✓	**56.8**	**51.8**	**45.6**	**59.1**	**51.9**	**46.5**	**65.4**	**53.8**	**47.5**	21.6
SiamBAN [21]	CVPR 20	✗	62.1	55.3	47.5	56.9	50.3	43.1	64.7	50.9	43.7	53.9
SiamRPN++-RBO [27]	CVPR 22	✗	63.3	57.6	49.5	58.5	52.9	45.2	68.2	54.8	46.9	54.0
UDAT-BAN [4]	CVPR 22	✓	63.3	56.6	47.9	56.4	50.0	42.1	69.4	54.6	46.9	55.1
OSTrack [20]	ECCV 22	✗	67.8	61.6	55.0	66.0	58.9	52.9	72.2	60.9	53.9	92.1
SAM-DA [9]	ICARM 23	✓	62.3	56.2	47.9	59.2	52.9	45.4	67.0	53.6	46.0	53.9
SmallTrack [28]	TGRS 23	✗	65.6	52.3	44.9	56.0	49.7	42.5	65.6	52.3	44.9	53.9
DCPT [18]	ICRA 24	✓	70.3	63.9	57.1	67.1	59.9	53.7	69.4	58.4	52.0	92.9
DPTracker-B	**Ours**	✓	**72.3**	**65.2**	**58.1**	**69.8**	**62.2**	**55.8**	**73.9**	**62.5**	**55.9**	94.0

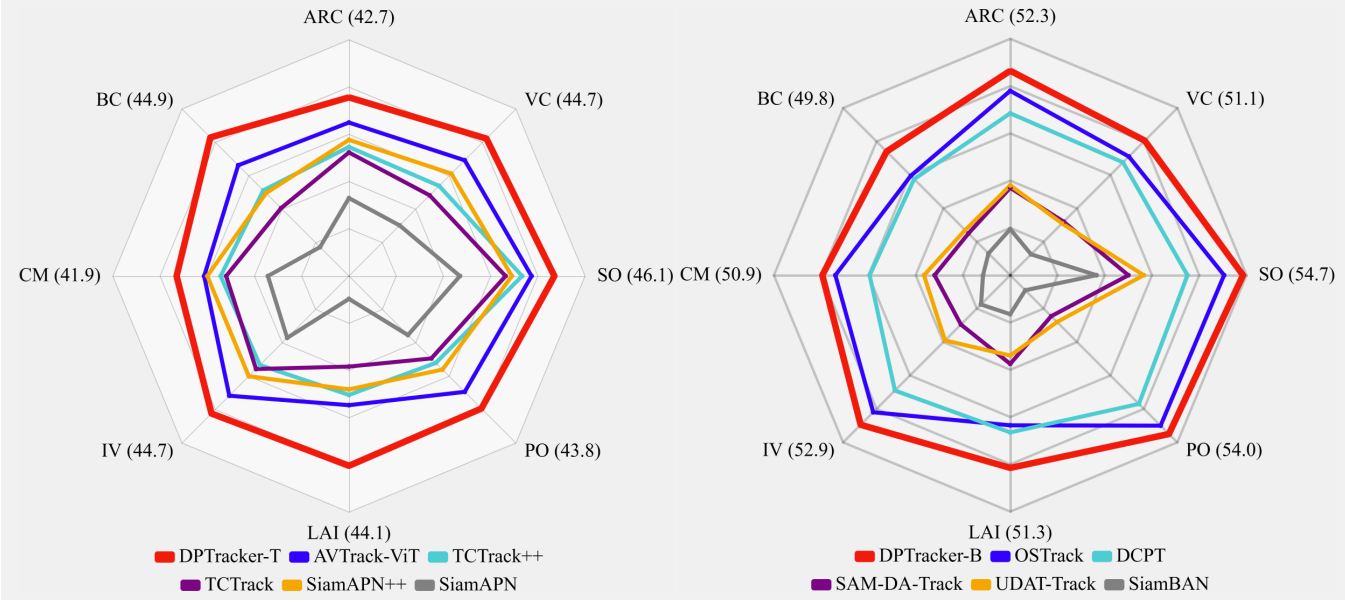


Fig. 5. Attribute-based tracking performance evaluation. As shown in the left figure, DPTracker-T consistently achieves the best performance across all 8 attributes on NAT2021-test [4], outperforming 5 other lightweight trackers [5], [23]–[26]. In the right figure, DPTracker-B also demonstrates substantial performance improvements compared to other well-performing trackers [4], [9], [18], [20], [21].

contribute to robust nighttime UAV tracking.

E. Real-World Tests

To assess real-world performance, a workstation equipped with an NVIDIA RTX 3080Ti GPU serves as the ground control station (GCS). The Parrot UAV captures images at 10 frames per second and transmits them to the GCS via WiFi. Upon manual initialization of the target bounding box in the initial frame, the tracker maintains a real-time inference speed of **54** FPS, facilitating continuous target localization and transmitting target positions back to the UAV. As presented in Fig. 6, tracking performance is evaluated using the center location error (CLE), where values below 20 are regarded as successful localization. The proposed DPTracker-T demonstrates reliable tracking across diverse nighttime conditions. Test 1 is conducted under low ambient illumination, where the partial out-of-view of the target further compounds the tracking difficulty. Test 2 is primarily challenged by camera motion, which introduces significant trajectory variations and appearance blur. Test 3 involves a street-crossing scene characterized by background clutter. The proposed tracker demonstrates robust tracking performance under the challenging nighttime scenarios.

TABLE II

ABLATION STUDY OF THE PFI, PIP, AND DVP. THE PERFORMANCE ON UAVDARK135 VERIFIES THE CONTRIBUTION OF EACH COMPONENT.

PFI	PIP	DVP	Prec.(%)	Δ (%)	Succ.(%)	Δ (%)
✗	✗	✗	67.8	-	55.0	-
✓	✗	✗	71.4	+5.3	57.5	+4.5
✓	✓	✗	71.9	+6.0	57.8	+5.1
✓	✓	✓	**72.3**	**+6.6**	**58.1**	**+5.6**

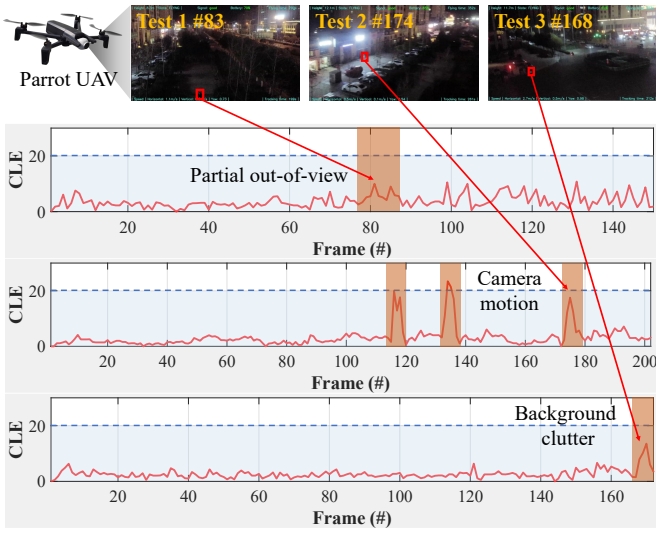


Fig. 6. Real-world UAV tracking tests under nighttime conditions. Regions in blue, where the CLE is less than 20, are regarded as successful tracking cases, while the orange regions represent challenging tracking conditions.

V. CONCLUSIONS

This work proposes a dual prompt-driven feature encoding method to learn illumination and view-adaptive representations for nighttime UAV tracking. Prompt–feature interaction plays a central role in reinforcing the mutual adaptation between prompts and visual features for enhanced representation robustness. Built upon this interaction method, the pyramid illumination prompter and dynamic viewpoint prompter further strengthen the model's ability to accommodate complex illumination conditions and dynamic viewpoint changes. Comprehensive experiments and ablation studies verify the effectiveness of these components. Future research will extend this adaptive prompting paradigm to broader adverse scenarios in autonomous aerial systems. In

summary, this study contributes to low-light object tracking for unmanned aerial vehicles in adverse conditions.

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