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Instance-level Visual Active Tracking with Occlusion-Aware Planning

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Abstract

*Visual Active Tracking (VAT) aims to control cameras to follow a target in 3D space, which is critical for applications like drone navigation and security surveillance. However, it faces two key bottlenecks in real-world deployment: confusion from visually similar distractors caused by insufficient instance-level discrimination and severe failure under occlusions due to the absence of active planning. To address these, we propose **OA-VAT**, a unified pipeline with three complementary modules. First, a training-free Instance-Aware Offline Prototype Initialization aggregates multi-view augmented features via DINOv3 to construct discriminative instance prototypes, mitigating distractor confusion. Second, an Online Prototype Enhancement Tracker enhances prototypes online and integrates a confidence-aware Kalman filter for stable tracking under appearance and motion changes. Third, an Occlusion-Aware Trajectory Planner, trained on our new `Planning-20k` dataset, uses conditional diffusion to generate obstacle-avoiding paths for occlusion recovery. Experiments demonstrate OA-VAT achieves 0.93 average SR on UnrealCV (+2.2% vs. SOTA TrackVLA), 90.8% average CAR on real-world datasets (+12.1% vs. SOTA GC-VAT), and 81.6% TSR on a DJI Tello drone. Running at 35 FPS on an RTX 3090, it delivers robust, real-time performance for practical deployment. The code is available at `https://github.com/SHWplus/OA-VAT`.*

1. Introduction

Visual Active Tracking (VAT) aims to dynamically control cameras to follow a specific target instance in 3D space [4, 12, 26, 39, 42, 51–55]. It is widely used in real-world applications such as navigation [16, 24, 43, 49] and security surveillance [14, 35, 46, 50]. Unlike passive visual tracking [1, 3, 5, 21, 38, 44, 47, 56] that operates on pre-recorded videos, VAT requires the agent to move the camera based on real-time visual observations. Passive visual tracking often falls short in the real world due to the dynamic nature of most targets. Thus, VAT offers a more practical yet challenging solution for real-world tracking applications.

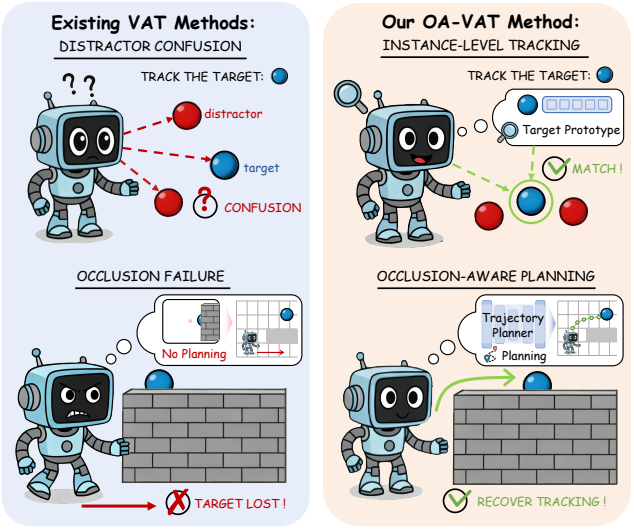

Figure 1. Comparison of existing VAT methods and OA-VAT. During offline initialization, we construct a target prototype to robustly match the target against distractors. During tracking, we employ a trajectory planner to recover the target under occlusions.

Existing VAT approaches are broadly categorized into reinforcement learning (RL)-based [12, 26, 39, 52, 55] and pipeline methods [4, 27, 42, 54]. RL-based methods learn end-to-end policies that map pixels to actions, enabling low-latency control without intermediate modules. However, they often struggle with sparse reward signals, leading to poor convergence in complex environments. Additionally, RL-based methods rely on simulation [11, 12, 32, 39] for policy training, which limits their deployment due to the sim-to-real gap. In contrast, pipeline methods decouple tracking into separate perception and control stages. These methods use pre-trained visual models [2, 6, 21, 22, 30, 41]

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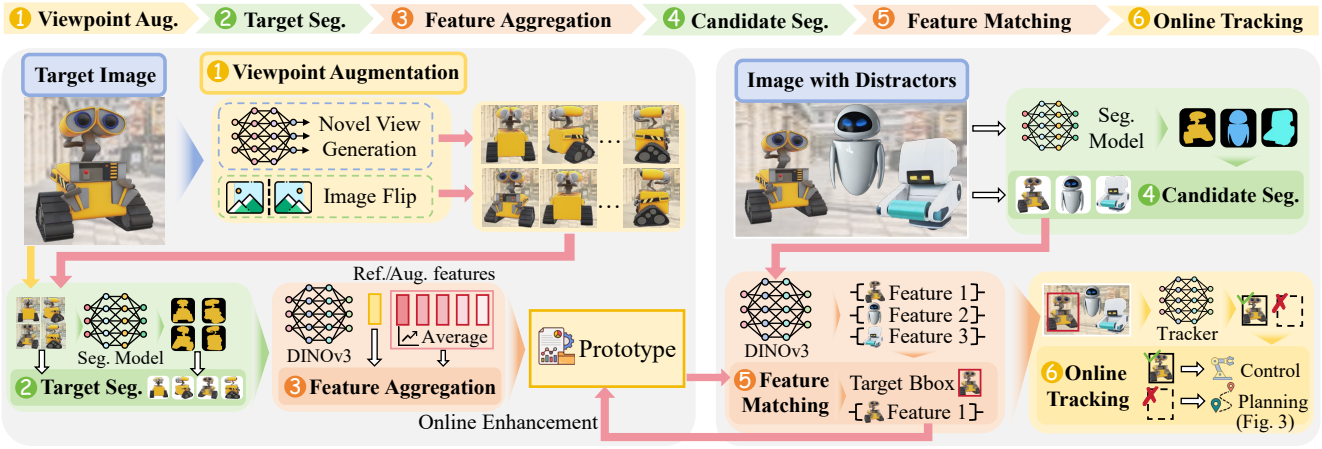


(a) Diagram of Instance-Aware Offline Prototype Initialization.

(b) Diagram of Online Prototype Enhancement Tracker.

Figure 2. Overview of Occlusion-Aware-VAT (OA-VAT). (a) Given a reference image, OA-VAT first constructs an instance-aware prototype offline by aggregating features from viewpoint augmentations. (b) At runtime, OA-VAT first detects the target via matching prototype and then tracks it online with prototype enhancement. When tracking fails, it activates the planning module (Fig. 3(b)) to recover target tracking.

for perception, enabling strong generalization to unseen environments. Consequently, pipeline VAT methods offer a more deployable alternative under real-world constraints.

Unfortunately, existing pipeline methods remain challenging in real scenarios, partly for the following reasons (Fig. 1). **1) Lack of instance-level tracking ability.** Real-world tracking often involves multiple similar distractors. However, most existing VAT methods [4, 12, 27, 39, 55] operate at the **category level** and struggle to distinguish specific target instances. **2) Missing active occlusion handling.** Most pipeline VAT methods [10, 27, 31] employ simple controllers (*e.g.*, PID [28]) that only center the target in the image, without considering occlusions. While simplifying system design, such controllers cannot navigate trackers around obstacles to recover the target, often causing failure.

To address these, we propose a pipeline VAT method called OA-VAT (see Fig. 2), which enables instance-level discrimination and active recovery of occluded targets. First, we introduce an **Instance-Aware Offline Prototype Initialization** module. It extracts discriminative prototype features from the target's reference image. Second, we propose an **Online Prototype Enhancement Tracker** that tracks the target by matching the prototype to current frames. It uses online prototype enhancement to handle target appearance changes and a confidence-aware Kalman filter for motion prediction. Third, we develop an **Occlusion-Aware Trajectory Planner** to recover tracking during occlusions. Trained on our new `Planning-20k` dataset, it actively guides the camera around obstacles to restore target visibility. Our main contributions are as follows:

- **A Robust Instance-Level Tracker.** We propose a training-free tracker that initializes a discriminative prototype from a reference image, enhances it online, and integrates a confidence-aware Kalman filter for robust tracking under appearance and motion changes.
- **An Active Occlusion-Aware Planner.** We develop a path planner trained on our new `Planning-20k` dataset that plans collision-free trajectories to recover occluded targets and generalizes to arbitrary unseen targets.
- **Extensive Validation.** Experiments on simulators, real-world images, and a drone demonstrate OA-VAT's state-of-the-art performance and real-time inference.

2. Task Definition

Visual Active Tracking (VAT) aims to dynamically control a camera to follow a specific target instance in 3D space. The tracking agent must cope with challenges such as distractors, occlusions, and highly dynamic environments. We formulate VAT as a continuous visual control problem, characterized by the observation space, action space, and success criterion described below, and solved by a VAT tracker.

Observation space $\mathcal{O}$. At each time step, the agent receives an RGB image $\mathcal{I}_t$ (*e.g.*, 160×120 pixels). Besides, a single reference image $\mathcal{I}_{ref}$, depicting the target instance to be tracked, is provided at the beginning of the episode.

Action space $\mathcal{A}$. The agent operates in a continuous action space $\mathcal{A} \in \mathbb{R}^4$, with $a_t = [v_f, v_l, v_v, \omega_y]^T$ representing linear velocities (forward, lateral, vertical) and yaw rotation.

VAT Tracker. We define a VAT tracker as an embodied agent parameterized by a policy π_θ, which maps visual observations to continuous control actions, i.e.,

$$a_t = \pi_\theta(\mathcal{I}_t, \mathcal{I}_{ref}). \tag{1}$$

Success criterion. We define a success criterion when the tracker keep the target instance centered in the image for a long duration. Metrics are detailed in Sec. 4.1.

3. Handling Distractors and Occlusions in VAT

Visual active tracking in the real world is extremely challenging, primarily due to the prevalence of distractors and frequent occlusions. To address these challenges, we propose Occlusion-Aware VAT (**OA-VAT**), an instance-level tracking method with occlusion awareness, aiming to improve visual active tracking in complex real-world applications. As shown in Fig. 2, OA-VAT incorporates a training-free instance tracking module that distinguishes the target from distractors. Moreover, we train a planning policy capable of recovering occluded targets. (see Fig. 3).

3.1. Instance-Aware Offline Prototype Initialization

We seek to build a training-free extraction module to obtain discriminative prototype features of the target instance. While existing visual foundation models (*e.g.*, Grounding-DINO [25], SAM [19], DINOv3 [37]) excel at category-level detection and segmentation, they struggle to provide features that are sufficiently discriminative at the instance level. Consequently, directly representing the target with their raw features or masks often leads to confusion with distractors. To address this, we propose an offline module that extracts a robust prototype from foundation model outputs without any additional training. Furthermore, we provide theoretical analysis for its effectiveness in Sec. 3.4.

Given a reference image $\mathcal{I}_{ref}$ of the target, we apply viewpoint augmentations and construct a prototype that captures view-invariant features for robust tracking. Specifically, we augment $\mathcal{I}_{ref}$ with horizontal and vertical flips to increase appearance diversity, producing an augmented image set $\{\mathcal{I}_i\}_i$. For human targets, whose appearance varies significantly across viewpoints, we generate additional views using an off-the-shelf diffusion model [48] and augment them with the same flips. We then employ a segmentation model $\texttt{Seg}(\cdot)$ (we use YOLO-E [40] for its speed-performance balance) to obtain the target mask and crop the instance in the reference and augmented images. This produces a set of target crops $\tilde{\mathbf{I}} = \{\tilde{\mathcal{I}}_{ref}, \tilde{\mathcal{I}}_1, ..., \tilde{\mathcal{I}}_N\}$, where $\tilde{\mathcal{I}}_i$ denotes the target crop of $\mathcal{I}_i$.

Subsequently, we employ a feature descriptor $\texttt{Desc}(\cdot)$, specifically DINOv3 [37] followed by global average pooling to extract features from the set $\tilde{\mathbf{I}}$:

$$\mathbf{f}_{ref} = \texttt{Desc}(\tilde{\mathcal{I}}_{ref}),\ \mathbf{f}_i = \texttt{Desc}(\tilde{\mathcal{I}}_i),\ i = 1, \dots, N, \quad (2)$$

where $\mathbf{f}_{ref}$ and $\mathbf{f}_i$ are the feature vectors for the reference and the i-th augmented image, respectively. The initial visual prototype $\tilde{\mathbf{f}}$ is obtained by averaging the original feature with the mean feature of the augmented set as follows:

$$\tilde{\mathbf{f}} = \frac{\mathbf{f}_{ref} + \frac{1}{N}\sum_{i=1}^{N} \mathbf{f}_i}{\|\mathbf{f}_{ref} + \frac{1}{N}\sum_{i=1}^{N} \mathbf{f}_i\|_2}. \quad (3)$$

The complete pipeline for the instance-aware offline prototype initialization module is shown in Fig. 2(a).

Algorithm 1 Online Prototype Enhancement Tracker

Require: Frame $\mathcal{I}_t$, prototype $\tilde{\mathbf{f}}'$, bounding box $\mathbf{b}_t$, seg. model $\texttt{Seg}(\cdot)$, feature descriptor $\texttt{Desc}(\cdot)$, similarity threshold η_s, confidence threshold η_c, tracker $\mathcal{T}$
Ensure: Updated prototype $\tilde{\mathbf{f}}'$, predicted box $\mathbf{b}_{t+1}$

```
if b_t = ∅ then
    Obtain M candidate masks: {M^i}_{i=1}^M ← Seg(I_t)
    Crop candidates: I^i_cand ← I_t ⊙ M^i, i ∈ {1, ..., M}
    Extract f^i_cand ← Desc(I^i_cand), compute S via Eq. (4)
    Find best candidate: i* ← arg max_i S_i, b_{t+1} ← ∅
    if S_{i*} > η_s then
        b_{t+1} ← bounding box of I^{i*}_cand
    end if
else
    Update tracker T with I_t and b_t
    Get confidence c_t and bounding box z_t from T
    Predict x̂_{t|t-1} via Eq. (6) and b_{t+1} ← H x̂_{t|t-1}
    if c_t < η_c then
        z_t ← ∅
    else
        Update state x̂_{t|t} via Eq. (7)
        Get predicted bounding box b_{t+1} ← H x̂_{t|t}
        Extract normalized target feature f̂_tar
        Enhance Prototype f̃' via Eq. (5)
    end if
end if
return f̃', b_{t+1}
```

3.2. Online Prototype Enhancement Tracker

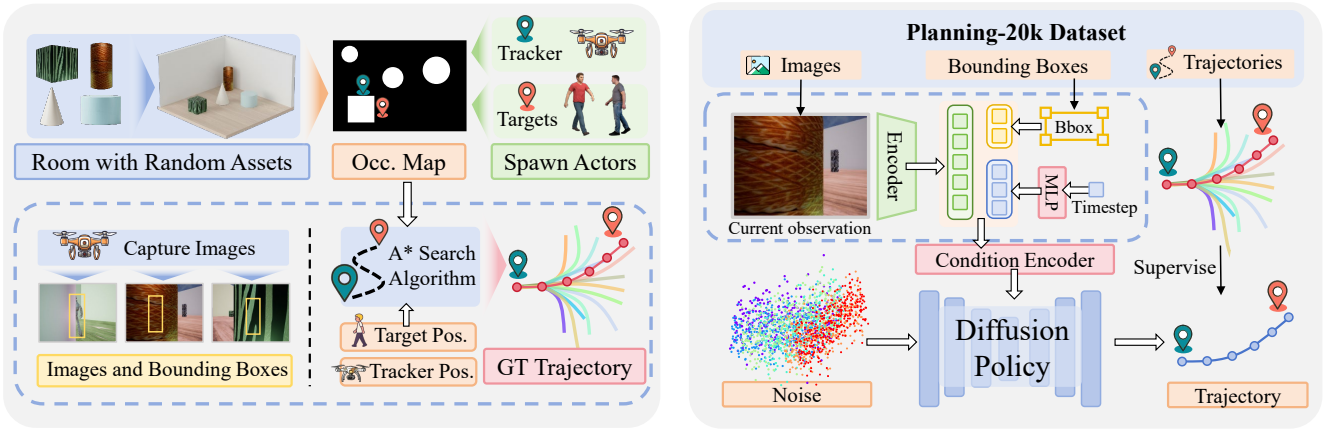
In the VAT setting, no initial bounding box is given, and the target's appearance and motion vary greatly during tracking. To address this, we first detect the target by matching the initialized prototype to the current frame. During tracking, we enhance the prototype online using new frames and predict the target's future motion to maintain robustness.

Online Visual Prototype Enhancement. Our enhancement strategy operates based on the current tracking state. If the tracker is uninitialized (i.e., the current bounding box $\mathbf{b}_t = \varnothing$), we start a target detection procedure. For each incoming observation frame $\mathcal{I}_t$, we first employ the segmentation model $\texttt{Seg}(\cdot)$ to extract M candidate object masks belonging to the target category. These candidates are then cropped from the frame, producing a set of image crops $\mathcal{I}_{\text{cand}} = \{\mathcal{I}^1_{\text{cand}}, ..., \mathcal{I}^M_{\text{cand}}\}$. Each crop is then processed by $\texttt{Desc}(\cdot)$ to obtain feature $\mathbf{f}^i_{\text{cand}}$ for the i-th candidate.

We then compute the cosine similarity between current visual prototype $\tilde{\mathbf{f}}'$ and each candidate feature $\mathbf{f}^i_{\text{cand}}$ as:

$$S(\tilde{\mathbf{f}}', \mathbf{f}^i_{\text{cand}}) = \frac{\tilde{\mathbf{f}}' \cdot \mathbf{f}^i_{\text{cand}}}{\|\tilde{\mathbf{f}}'\|_2 \|\mathbf{f}^i_{\text{cand}}\|_2}, \quad (4)$$

where $\tilde{\mathbf{f}}'$ is initialized as $\tilde{\mathbf{f}}$. The candidate with the highest similarity that exceeds a predefined threshold η_s is identified as the target instance. Once a candidate is matched, its



(a) Diagram of the Planning-20k Data Collection Pipeline.

(b) Diagram of the Occlusion-Aware Planning Module.

Figure 3. Overview of the proposed Occlusion-Aware Trajectory Planner. The planner denoises a random trajectory into a feasible recovery path conditioned on image observations and a predicted target bounding box, enabling target-agnostic trajectory planning.

bounding box and the current frame $\mathcal{I}_t$ are used to initialize an object tracker [45] $\mathcal{T}$ for precise localization.

During tracking, the tracker captures the target from varying viewpoints. These frames provide online features for enhancing the visual prototype. Specifically, we extract the normalized target feature $\tilde{\mathbf{f}}_{\text{tar}}$ via $\texttt{Desc}(\cdot)$, and update the prototype via an exponential moving average (EMA):

$$\tilde{\mathbf{f}}' \leftarrow \beta\tilde{\mathbf{f}}' + (1-\beta)\hat{\mathbf{f}}_{\text{tar}}, \tag{5}$$

where β is the EMA momentum. To avoid slowing down the online tracking, the prototype is updated in a separate thread. This strategy ensures the prototype continuously adapts to the appearance variations, maintaining discriminability over long tracking sequences.

Confidence-Aware Kalman Filter. To handle rapidly changing target motions, we design a confidence-aware Kalman filter that adapts the filter parameters based on the tracker's confidence to ensure robust motion prediction. We define the state vector as $\mathbf{x}_t = [x, y, w, h, \dot{x}, \dot{y}, \dot{w}, \dot{h}]^T$, representing the bounding box and its derivatives. The standard Kalman filter [18] operates via a predict-update cycle, where the state prediction $\hat{\mathbf{x}}_{t|t-1}$ is given by:

$$\hat{\mathbf{x}}_{t|t-1} = \mathbf{F}\hat{\mathbf{x}}_{t-1|t-1}, \tag{6}$$

where $\mathbf{F}$ is the state transition matrix. Given the current confidence c_t and bounding box $\mathbf{z}_t$ from tracker $\mathcal{T}$, the state is updated when c_t exceeds the threshold η_c:

$$\hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}_t\left(\mathbf{z}_t - \mathbf{H}\hat{\mathbf{x}}_{t|t-1}\right), \tag{7}$$

where $\mathbf{H}$ is the observation matrix and $\mathbf{K}_t$ is the Kalman gain, given by:

$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}^\top\left(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^\top + \mathbf{R}_t\right)^{-1}, \tag{8}$$

where $\mathbf{P}$ denotes the state covariance, and $\mathbf{R}_t$ is the measurement noise covariance. When the noise is large, the uncertainty in $\mathbf{z}_t$ increases, leading to a smaller $\mathbf{K}_t$, which assigns less weight to the current observation. The predicted bounding box can be obtained from $\hat{\mathbf{x}}_{t|t}$: $\mathbf{b}_{t+1} \leftarrow \mathbf{H}\hat{\mathbf{x}}_{t|t}$.

Our confidence-aware Kalman filter adapts the noise $\mathbf{R}_t$ according to the confidence c_t. We hypothesize that c_t reflects the uncertainty of the current observation. Thus, the noise variance $\sigma^2(\cdot)$ is modeled as a function of c_t:

$$\mathbf{R}_t = \sigma^2(c_t)\mathbf{I}, \quad \sigma^2(c_t) = \frac{1}{1+e^{\lambda\cdot(c_t-\gamma)}}, \tag{9}$$

where λ and γ are hyperparameters. This sigmoid mapping reduces σ^2 and increases trust in the observation when c_t exceeds γ, while enlarging σ^2 when c_t is low. Consequently, at low confidence, the Kalman gain $\mathbf{K}_t$ is suppressed, making the filter rely more on its internal state prediction than on the noisy observation. This mechanism also allows the filter to continue predicting the target motion as in Eq. (6) during tracking failures, increasing the likelihood of re-acquiring the target. If no $\mathbf{z}_t$ is available for many consecutive frames, the planning module is triggered (see Sec. 3.3). The pseudocode is shown in Algorithm 1.

3.3. Occlusion-Aware Trajectory Planner

Another key challenge in open-world active tracking is frequent occlusion. Existing pipeline methods often use PID controllers [28] that steer the tracker with the image-plane distance between the target and the center. While effective for direct pursuit, these methods fail under occlusion, as they cannot plan trajectories to navigate around obstacles.

To address this, we propose a planning module that generates recovery trajectories via imitation learning. Since expert demonstrations under occlusion are unavailable, we introduce `Planning-20k`, a synthetic dataset collected in UnrealCV [32]. Using this data, we train a diffusion model to predict tracker trajectories conditioned on visual observations and the target bounding box. This design makes the

policy inherently *target-agnostic*, enabling zero-shot generalization to arbitrary unseen targets.

Data Collection. The design of our `Planning-20k` dataset is central to learning a target-agnostic occlusion-recovery policy. As illustrated in Fig. 3(a), we generate data in UnrealCV's `SimpleRoom` environment as follows.

We first construct each map by randomly placing obstacles in an empty room and building a 2D occupancy map. To simulate occlusions, we randomly select an obstacle and spawn the target on one of its bounding box edges e_i. The tracker is then placed on an adjacent edge to e_i to capture an RGB image and the target bounding box. Samples where the target is fully visible are discarded, ensuring only non-trivial planning scenarios. To enhance visual diversity, we apply domain randomization to illumination and obstacle textures using a texture dataset [8]. Expert trajectories are then obtained via A* search algorithm [17] on the occupancy map. The final dataset contains 20k samples, including 8k with default textures and 12k with randomized ones. Each sample consists of an RGB image, a target bounding box, and the corresponding expert trajectory.

Data Diversity. Our `Planning-20k` covers common occlusion structures in real scenes. **(1)** Single-side occlusion blocks one side of the view. **(2)** Double-side involves occlusions on both sides, leaving a central gap for navigation. **(3)** Corridor-type occlusion includes obstacles on three sides, mimicking entry into a narrow hallway from a room.

Occlusion-Aware Planning Module. To achieve robust trajectory planning under occlusions, we propose a planning module inspired by Diffusion Policy [7]. We formulate the trajectory planning problem as a conditional denoising diffusion process. Previous diffusion policies [7] conditioned solely on visual observations often overfit the visual appearance of specific targets, limiting their generalization when the target changes. *In contrast*, OA-VAT incorporates target bounding boxes as an explicit condition. This guides the model to learn *target-agnostic* trajectory planning, thereby enabling robust generalization to unseen targets.

Formally, let $\mathbf{A}_t$ denotes trajectory points over a horizon T_p. We model the conditional distribution $p(\mathbf{A}_t|\mathcal{I}_t, \mathbf{b}_t)$ where $\mathcal{I}_t$ is the image and $\mathbf{b}_t$ is the target bounding box. The diffusion process starts from noise $\mathbf{A}_t^K \sim \mathcal{N}(0, \mathbf{I})$ and iteratively denoises for K steps via:

$$\mathbf{A}_t^{k-1} = \alpha\left(\mathbf{A}_t^k - \phi\epsilon_\theta(\mathcal{I}_t, \mathbf{b}_t, \mathbf{A}_t^k, k)\right) + \mathcal{N}(0, \sigma^2\mathbf{I}), \quad (10)$$

where ϵ_θ is a noise prediction network [34] that estimates the gradient of the action score function, and α, ϕ, σ are noise scheduling function of iteration k [29]. We use the mean squared error (MSE) to define the training objective:

$$\mathcal{L} = \mathbb{E}_{k, \mathbf{A}_t^0, \boldsymbol{\varepsilon}}\left[\|\boldsymbol{\varepsilon} - \epsilon_\theta(\mathcal{I}_t, \mathbf{b}_t, \mathbf{A}_t^0 + \boldsymbol{\varepsilon}, k)\|^2\right], \quad (11)$$

where ϵ is the random noise. $\mathcal{L}$ encourages the network to reconstruct the noise added to the ground-truth trajectory.

During online tracking, when the tracker (in Sec. 3.2) becomes unreliable, *i.e.*, $c_t < \eta_c$, we employ the confidence-aware Kalman filter in Eq. (6) to predict the bounding box $\mathbf{b}_t$ of the occluded target. $\mathbf{b}_t$ is then used as the conditioning input to our planner, generating a recovery trajectory.

Why our planner generalizes well. Our planner generalizes robustly by using bounding boxes to model physical spatial rules, bypassing visual textures and the need for large-scale photorealistic data.

3.4. Theoretical Guarantees on Instance Prototype

For any target instance T_k, we define its true feature manifold M_k as the set of all features extracted by $\texttt{Desc}(\cdot)$ under arbitrary imaging conditions. From this manifold, the normalized reference features of T_k are obtained via Eq. (2) and denoted by the set F_k^*. For each reference feature $f_k^* \in F_k^*$, we generate a corresponding set of multi-view augmented features $\{f_{k,i}\}_{i=1}^N$. The instance-aware prototypes are then derived via Eq. (3) and form the set $\hat{F}_k$. For any manifold M, $\mathbb{E}_{g\sim M}[\cdot]$ denotes expectation over M.

Proposition 1 *Under the assumptions that (i) multi-view augmented features $\{f_{k,i}\}_{i=1}^N$ better cover the true feature manifold M_k than the reference feature f_k^* and (ii) features from the same target are cohesive while those from different targets are well-separated, for any two distinct targets $T_k \neq T_j$, the minimum squared distance between any pair of $(\hat{f}_k, \hat{f}_j)$ sampled from $\hat{F}_k$ and $\hat{F}_j$ is larger than that between any pair of (f_k^*, f_j^*) sampled from F_k^* and F_j^*:*

$$\min_{\hat{f}_k\in\hat{F}_k, \hat{f}_j\in\hat{F}_j} \|\hat{f}_k - \hat{f}_j\|_2^2 \geq \min_{f_k^*\in F_k^*, f_j^*\in F_j^*} \|f_k^* - f_j^*\|_2^2. \quad (12)$$

For the proof of Proposition 1, please refer to the Appendix. Proposition 1 shows that the instance-aware offline prototype initialization module (Sec. 3.1) improves inter-instance separation by aggregating multi-view features, producing prototypes more discriminative than the original foundation model features, as validated by Fig. 4.

4. Experiment

4.1. Experimental Settings

Experimental Setup. We evaluate OA-VAT in a zero-shot setting on two state-of-the-art VAT benchmarks: UnrealCV [32] and DAT [39]. In UnrealCV, we test OA-VAT on 3 challenging maps with distractors (Parking Lot (2D), UrbanCity (4D), ComplexRoom (4D)) and 5 single-target maps. In DAT, we perform evaluations under daytime condition across all six scenes, comparing OA-VAT with within-scene trained models. We further validate OA-VAT on real-world image datasets including VOT [20], DTB70 [23], and UAVDT [13], and deploy it on a *DJI Tello* drone [9] for real-world evaluation. *Implementation details and hyperparameter analysis are provided in the Appendix.*

Table 1. Results in UnrealCV environments containing **distractors**. **Bold** represents the best while underline represents the second. TrackVLA [42] does not report AR and its training code and checkpoints are not publicly available, so we cannot reproduce this metric.

Tracker	Publication	Parking Lot (2D)			UrbanCity (4D)			ComplexRoom (4D)			Average			Params.
		$AR\uparrow$	$EL\uparrow$	$SR\uparrow$	$AR\uparrow$	$EL\uparrow$	$SR\uparrow$	$AR\uparrow$	$EL\uparrow$	$SR\uparrow$	$AR\uparrow$	$EL\uparrow$	$SR\uparrow$	
DiMP [4]	ICCV 2019	111	271	0.24	170	348	0.32	97	307	0.26	126	309	0.27	$26M$
SARL [26]	TPAMI 2019	53	237	0.12	74	221	0.16	22	263	0.15	50	240	0.14	$2M$
AD-VAT [51]	ICLR 2019	43	232	0.13	32	204	0.06	16	223	0.16	30	220	0.12	$4M$
AD-VAT+ [52]	TPAMI 2019	35	166	0.08	89	245	0.11	35	262	0.18	53	224	0.12	$4M$
TS [53]	ICML 2021	186	331	0.39	227	381	0.51	250	401	0.54	221	371	0.48	$7M$
EVT [55]	ECCV 2024	192	425	0.63	272	472	0.92	354	479	0.88	273	459	0.81	$748M$
FAn [27]	RAL 2024	126	301	0.28	167	334	0.30	189	351	0.29	161	329	0.29	$132M$
FAn+SAM2 [33]	ICLR 2025	170	349	0.40	201	407	0.55	262	422	0.61	211	393	0.52	$122M$
TrackVLA [42]	CoRL 2025	-	467	0.90	-	476	0.92	-	479	0.91	-	474	0.91	$> 7B$
Ours	CVPR 2026	**392**	**482**	**0.93**	**385**	**486**	**0.95**	**392**	**481**	**0.92**	**390**	**483**	**0.93**	$584M$

Table 2. Performance on DAT benchmark under within scene setting.

Tracker	Publication	citystreet		desert		village	
		$CR\uparrow$	$TSR\uparrow$	$CR\uparrow$	$TSR\uparrow$	$CR\uparrow$	$TSR\uparrow$
SARL [26]	TPAMI 2019	$49_{\pm 3}$	$0.25_{\pm 0.02}$	$9_{\pm 1}$	$0.06_{\pm 0.00}$	$46_{\pm 5}$	$0.23_{\pm 0.03}$
D-VAT [12]	RAL 2024	$48_{\pm 8}$	$0.26_{\pm 0.02}$	$47_{\pm 13}$	$0.26_{\pm 0.04}$	$44_{\pm 8}$	$0.22_{\pm 0.05}$
GC-VAT [39]	NeurIPS 2025	$279_{\pm 110}$	$0.80_{\pm 0.30}$	$307_{\pm 124}$	$\mathbf{0.84}_{\pm 0.29}$	$239_{\pm 134}$	$0.73_{\pm 0.32}$
Ours	CVPR 2026	$\mathbf{310}_{\pm 2}$	$\mathbf{0.83}_{\pm 0.01}$	$\mathbf{311}_{\pm 3}$	$0.83_{\pm 0.01}$	$\mathbf{307}_{\pm 2}$	$\mathbf{0.83}_{\pm 0.01}$
Tracker	Publication	downtown		lake		farmland	
		$CR\uparrow$	$TSR\uparrow$	$CR\uparrow$	$TSR\uparrow$	$CR\uparrow$	$TSR\uparrow$
SARL [26]	TPAMI 2019	$54_{\pm 5}$	$0.29_{\pm 0.01}$	$47_{\pm 3}$	$0.24_{\pm 0.02}$	$60_{\pm 25}$	$0.23_{\pm 0.01}$
D-VAT [12]	RAL 2024	$9_{\pm 1}$	$0.06_{\pm 0.01}$	$46_{\pm 8}$	$0.26_{\pm 0.06}$	$13_{\pm 1}$	$0.07_{\pm 0.00}$
GC-VAT [39]	NeurIPS 2025	$203_{\pm 119}$	$0.65_{\pm 0.30}$	$181_{\pm 116}$	$0.61_{\pm 0.31}$	$243_{\pm 117}$	$0.68_{\pm 0.32}$
Ours	CVPR 2026	$\mathbf{370}_{\pm 3}$	$\mathbf{0.99}_{\pm 0.01}$	$\mathbf{318}_{\pm 10}$	$\mathbf{0.84}_{\pm 0.02}$	$\mathbf{310}_{\pm 3}$	$\mathbf{0.83}_{\pm 0.02}$

Table 3. Average results of VAT trackers in UnrealCV (details in Appendix).

Tracker	Average		
	$AR\uparrow$	$EL\uparrow$	$SR\uparrow$
DiMP [4]	204	367	0.58
SARL [26]	240	394	0.57
AD-VAT [51]	238	416	0.62
AD-VAT+ [52]	307	454	0.76
TS [53]	312	474	0.86
RSPT [54]	329	478	0.92
EVT [55]	297	490	0.95
FAn [27]	237	462	0.90
FAn+SAM2 [33]	257	474	0.94
TrackVLA [42]	-	**500**	**1.00**
Ours	**391**	**500**	**1.00**

Metrics. In UnrealCV, we use three metrics: *Accumulated Reward (AR)* measures the average reward over 100 episodes. *Episode Length (EL)* denotes the average steps per episode, with early termination if the target remains out of view for more than 50 consecutive steps. *Success Rate (SR)* represents the proportion of success episodes where the tracker successfully follows the target for 500 steps. In DAT, *Cumulative Reward (CR)* measures the average total reward over 40 episodes, and *Tracking Success Rate (TSR)* denotes the success rate within 1,500 steps.

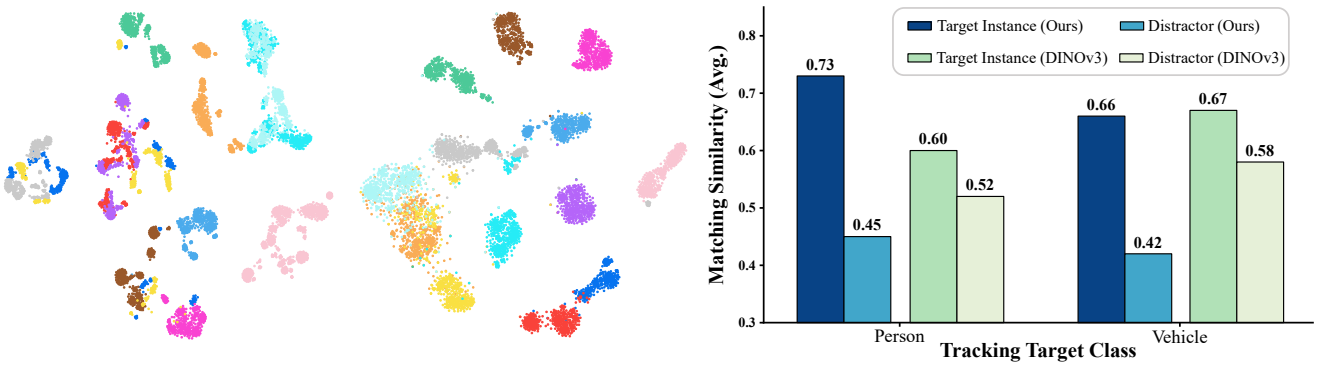
Baselines. We compare OA-VAT against 12 baselines, grouped into two categories: the RL-based trackers include SARL [26], AD-VAT [51], AD-VAT+ [52], TS [53], D-VAT [12], GC-VAT [39], and EVT [55]. The remaining methods follow a pipeline design: DiMP [4], RSPT [54], Follow Anything (FAn) [27], FAn+SAM2 [33], and TrackVLA [42]. *Related works are detailed in the Appendix.*

4.2. Comparison Experiments

Effectiveness and Efficiency in UnrealCV Environments with Distractors. We evaluate OA-VAT in UnrealCV [32] maps with similar distractors. As shown in Tab. 1, OA-VAT achieves the best performance among all compared methods, including the SOTA method TrackVLA [42]. Specifically, OA-VAT outperforms TrackVLA by 2.2% in average success rate while requiring far less computation. We train OA-VAT on single RTX 3090 GPU for 15 hours, compared to TrackVLA's 24×H100 GPUs for the same duration. Furthermore, OA-VAT has a model size of 584M, significantly smaller than both TrackVLA and EVT. It runs at **35 FPS** on an RTX 3090 GPU, notably faster than TrackVLA's 10 FPS on an RTX 4090 GPU, ensuring real-time performance.

Moreover, we also evaluate OA-VAT on distractor-free scenes. As shown in Tab. 3, OA-VAT achieves perfect performance ($SR = 1.00$) across all five scenes, maintaining the target in view for the full episode ($EL = 500$).

Effectiveness in DAT Environments. As shown in Tab. 2, OA-VAT consistently outperforms existing methods. It achieves average improvements of 32.6% in CR ($242 \rightarrow 321$) and 19.4% in TSR ($0.72 \rightarrow 0.86$) over GC-VAT [39]. The standard deviation of TSR is less than 0.02, indicating stable tracking performance. Notably, DAT targets are *vehicles*, which are unseen during training, demonstrating the strong zero-shot generalization of OA-VAT.



(a) t-SNE on prototypes of DINOv3. (b) t-SNE on prototypes of OA-VAT. (c) Average cosine similarity of prototype to target and to distractors.

Figure 4. Ablation study on the instance-aware offline prototype initialization module. In (a) and (b), each point represents a prototype feature extracted from single view of an instance, with all points from the same instance assigned the same color. (c) shows the similarity of the offline initialized prototype with the target instance versus distractors during online tracking.

Table 4. Results of ablation experiments on UnrealCV environments containing distractors.

Module	Setting	Parking Lot (2D)			UrbanCity (4D)			ComplexRoom (4D)			Average		
		AR	*EL*	*SR*	*AR*	*EL*	*SR*	*AR*	*EL*	*SR*	*AR*	*EL*	*SR*
Instance-Aware Offline Prototype Initialization	w/ DINOv3 [37] Prototype	384	481	0.92	369	443	0.84	370	454	0.85	374	459	0.87
	Ours	**392**	**482**	**0.93**	**385**	**486**	**0.95**	**392**	**481**	**0.92**	**390**	**483**	**0.93**
Online Visual Prototype Enhancement	w/o Online Enhancement	352	463	0.84	340	469	0.77	354	477	0.84	349	470	0.82
	w/ Average Enhancement	356	**485**	0.90	347	477	0.88	359	**481**	0.89	354	481	0.89
	Ours	**392**	482	**0.93**	**385**	**486**	**0.95**	**392**	**481**	**0.92**	**390**	**483**	**0.93**
Confidence-Aware Kalman Filter	w/o Kalman Filter	349	474	0.87	343	459	0.88	334	459	0.85	342	464	0.87
	w/ Linear Kalman Filter [18]	356	**488**	0.88	359	457	0.91	346	463	0.90	354	469	0.90
	Ours	**392**	482	**0.93**	**385**	**486**	**0.95**	**392**	**481**	**0.92**	**390**	**483**	**0.93**
Occlusion-Aware Trajectory Planner	w/o Planning (*i.e.*, PID [28])	345	478	0.83	360	470	0.88	353	460	0.84	353	469	0.85
	w/ EVT Planning [55]	308	472	0.82	303	475	0.88	360	482	0.90	324	476	0.87
	w/o Bounding Box	368	476	0.90	347	456	0.86	**396**	**484**	0.91	370	472	0.89
	Ours	**392**	**482**	**0.93**	**385**	**486**	**0.95**	392	481	**0.92**	**390**	**483**	**0.93**

4.3. Ablation Experiments

We validate our prototype initialization module (Sec. 3.1) on video datasets [15, 36] through qualitative and quantitative analysis. We then conduct ablation studies on three UnrealCV maps with distractors to evaluate the effectiveness of our prototype initialization, prototype enhancement, confidence-aware Kalman filter, and the planning module.

Effectiveness of Offline Prototype Initialization. We compare our prototype (Sec. 3.1) with raw DINOv3 features on *video 40* in PersonPath22 [36]. We extract a prototype for each target per frame. Fig. 4(a)-(b) shows that our prototypes are well-separated across instances, while DINOv3 features largely overlap. Quantitatively, we compute the average cosine similarity of prototype to targets and to distractors on *video 40* and all *car* videos in LaSOT [15]. OA-VAT achieves a similarity margin of 0.28 between person targets and distractors, larger than DINOv3's 0.08 (Fig. 4(c)). When applied to tracking, OA-VAT improves avg. SR by 6.9% relative to the DINOv3 baseline (Tab. 4(rows 1-2)).

Effectiveness of Online Prototype Enhancement. We compare our EMA-based enhancement against average-update and no-update variants. As shown in Tab. 4 (rows 3-5), it outperforms both no-update (+13.4% avg. SR) and average-update variant (+4.5% avg. SR), effectively balancing historical knowledge and recent observations.

Effectiveness of Confidence-Aware Kalman Filter. As shown in Tab. 4 (rows 6-8), OA-VAT improves avg. SR by 6.9% over the no-filter baseline, and outperforms the linear Kalman filter variant (+3.3% avg. SR), showing that state estimation helps correct the unreliable bounding boxes.

Effectiveness of Planning Module. We compare our planner with three alternatives: no planning (PID [28]), EVT planning [55] module based on offline RL, and a planner trained without bounding boxes as input. As shown in Tab. 4 (rows 9-12), OA-VAT achieves an average SR of 0.93, outperforming EVT by 6.9% and the variant without bounding box input by 4.5%. This confirms that bounding box guidance enhances planning robustness, and our OA-VAT can effectively recover trajectories of occluded targets.

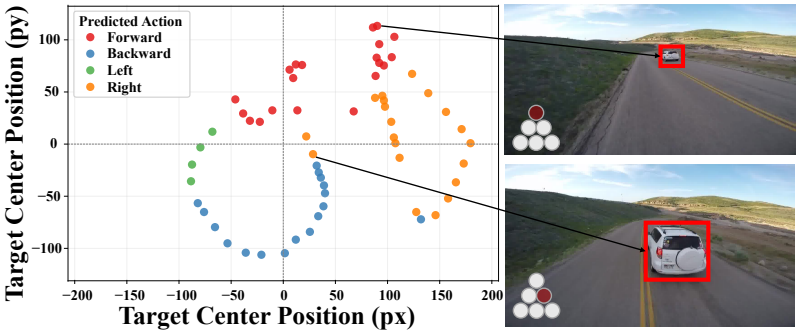


Figure 5. Results on real-world images of the *Car8* video in DTB70 [23] dataset.

Table 5. Effectiveness of OA-VAT on real-world image evaluation. We select eight videos from each of VOT [20], DTB70 [23] and UAVDT[13] datasets.

Tracker	Average Correct Action Rate		
	VOT [20]	DTB70 [23]	UAVDT [13]
Random	0.413	0.426	0.421
ORTrack [45]	0.661	0.781	0.879
ORTrack (w/o bbox)	0.260	0.380	0.296
FAn [27]	0.720	0.719	0.592
GC-VAT [39]	0.795	0.833	0.802
Ours	**0.879**	**0.900**	**0.945**

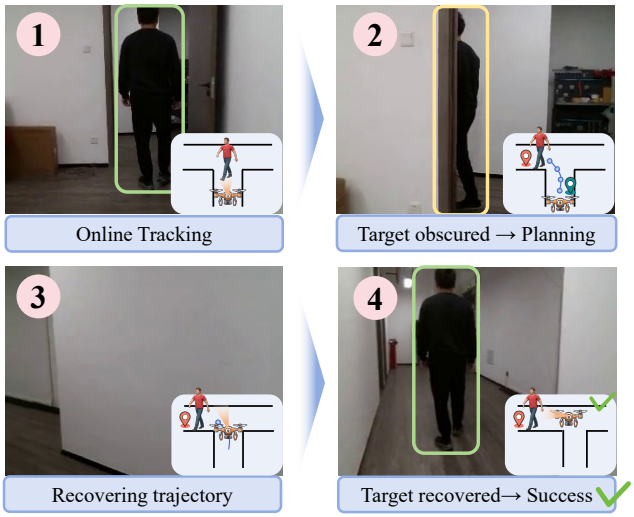
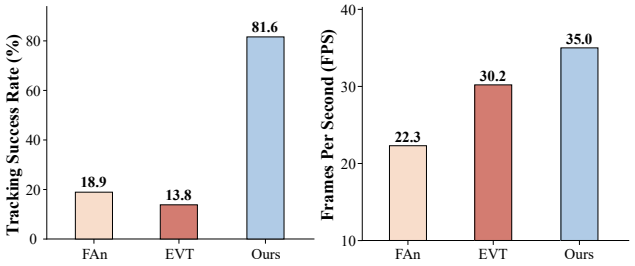


Figure 6. Recovery of prolonged occlusion on a *DJI Tello* drone.



(a) Success rate on real drones. (b) FPS on real drones.

Figure 7. Experiment results on real drone *DJI Tello*.

4.4. Experiments in Real-world Scenarios

Effectiveness on real-world images. To assess OA-VAT 's transferability to real-world scenarios, we follow the setting of [39] and perform zero-shot evaluation on 8 videos each from VOT [20], DTB70 [23], and UAVDT [13]. Although camera control is unavailable in these videos, we can feed frames into the model and verify whether the predicted action would move the target toward the image center.

Qualitative results on video *Car8* from DTB70 dataset are shown in Fig. 5. Each point denotes the target's location in the image, with its color indicating the predicted action. When the target deviates from the image center, OA-VAT correctly predicts actions to steer it back. Quantitatively, we use Correct Action Rate (CAR), i.e., the action-prediction accuracy, to evaluate the performance. As shown in Tab. 5, OA-VAT achieves an avg. CAR of 90.8%, outperforming GC-VAT [39] by 12.1%. *See Appendix for more results.*

To further evaluate robustness, we compare OA-VAT with ORTrack [45]. Despite requiring ground-truth bounding box initialization, ORTrack underperforms our method by 13.4% (0.774 *vs.* 0.908, Tab. 5) and collapses completely when given only a reference image.

Effectiveness on real robots. To assess the real-world applicability of OA-VAT, we deploy it on a *DJI Tello* drone [9]. During operation, the drone transmits H.264 video streams over Wi-Fi to a ground station equipped with an NVIDIA RTX 3090 GPU. The station then decodes the video, runs OA-VAT to generate control commands, and sends them back to the drone for closed-loop tracking.

We evaluate OA-VAT in two settings. In scenarios with distractors, OA-VAT locates and re-identifies the designated target after temporary occlusions. Under prolonged occlusion, OA-VAT navigates around obstacles to recover the target (Fig. 6), whereas EVT [55] and FAn [27] lose the target permanently. Moreover, We adopt Tracking Success Rate (TSR) to quantify tracking performance. As shown in Fig. 7(a), OA-VAT achieves a TSR of 81.6%, far surpassing the best baseline (18.9%). Furthermore, as shown in Fig. 7(b), OA-VAT runs at 35.0 FPS, enabling real-time operation in dynamic scenes. *See Appendix for more results.*

5. Conclusion

In this paper, we propose a pipeline VAT method, called OA-VAT. Specifically, we introduce an offline prototype initialization module to mitigate distractor confusion. Then we propose an online tracker that enhances prototypes online and integrates a confidence-aware Kalman filter for stable tracking. Moreover, we develop a planner trained on our `Planning-20k` dataset, which plans trajectories to recover occluded targets. Experiments on simulators, real-world images, and a drone demonstrate OA-VAT's state-of-the-art performance and real-time inference.

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