Diffusion-Driven Deblurring Motion in High-Mobility UAV Systems

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Abstract

Simultaneous motion of both unmanned aerial vehicles (UAVs) and ground-level targets—such as pedestrians—introduces complex motion blur in captured images, severely degrading visual quality and tracking accuracy. This paper presents a diffusion-based deblurring approach tailored for high-mobility UAV scenarios. We model the motion blur formation as a forward diffusion process and leverage a learned reverse process via denoising diffusion probabilistic models (DDPMs) to restore sharp images. Our method outperforms state-of-the-art deblurring techniques on synthesized motion blur datasets in terms of PSNR, SSIM, and object detection accuracy. This work enables more robust UAV-based surveillance, especially in dynamic, real-world settings.

Keywords: unmanned aerial vehicle, Deblurring Motion, High Mobility, GAN

I. Introduction

Unmanned Aerial Vehicles (UAVs) have emerged as crucial platforms for real-time surveillance, environmental monitoring, and security operations due to their mobility, flexibility, and increasing onboard intelligence [1]. Applications such as agricultural land protection, wildlife intrusion detection, and perimeter surveillance demand reliable target tracking under dynamic flight conditions, often involving rapid UAV movement and simultaneous motion of ground-level subjects, such as animals or humans [1], [2]. However, UAV footage in such high-mobility contexts frequently suffers from severe motion blur, which is introduced not only by the motion of the UAV itself but also by the independent movement of tracked objects. This dual-motion blur poses significant challenges to object detection, classification, and tracking accuracy—especially when edge-computing constraints require the use of lightweight models or low-power embedded systems [2].

Traditional deblurring methods, including CNN-based and GAN-based models like DeblurGAN [3], have shown promising results in static or mildly dynamic settings. Yet, they often fail to generalize to complex aerial motion patterns, where blur trajectories are nonlinear and scene depth varies rapidly. Recent advancements in diffusion models offer a powerful generative alternative for image restoration tasks, as they model image corruption and recovery as a sequential probabilistic process [4].

Motivated by this, we propose a Diffusion-Driven Deblurring framework that reconstructs high-quality UAV-captured images by learning to reverse the stochastic blur formation process. Our method is evaluated on the REDS dataset, augmented with synthetic UAV and pedestrian motion, and demonstrates significant improvements over conventional deblurring approaches. The work is situated within the broader context of UAV-based sensing systems and contributes to emerging research in communication-aware aerial monitoring and low-latency scene reconstruction for edge AI systems [5].

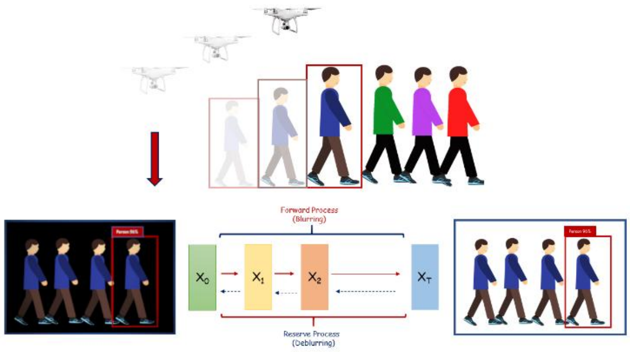

Figure 1 Overall proposed scenario

II. Proposed System and Methodology

a. **Overview:** Our method models blur as a progressive corruption of an image X_0 to a blurred frame X_T as show in Fig 1. and learns a reverse process to restore X_0 from X_T This framework effectively handles complex blur patterns resulting from joint UAV-target motion.

b. Diffusion Framework:

i. Forward Process: Gaussian noise is added to simulate motion blur across time steps:

$$q(X_t|X_{t-1}) = N\,(X_t;\, \sqrt{1-\beta_t}X_{t-1}, \beta_t I \qquad (1)$$

ii. Reverse Process: A neural network predicts the noise at each step to reconstruct the clean image:

$$P_\theta(X_{t-1}|X_t) = N(X_{t-1}; \mu_\theta(X_t,t), \textstyle\sum_\theta(X_t,t))$$

c. Dataset Details: We train and evaluate our model on the REDS dataset [5], a high-resolution video restoration benchmark offering paired sharp/blurred frames captured under dynamic scenes and high frame rates.

III. Experimental & Result Analysis:

To address dual-motion blur in UAV systems, we implement a DDPM with a U-Net backbone featuring skip connections, self-attention, and sinusoidal timestep embeddings. The model supports optional motion conditioning via optical flow or IMU data and performs denoising over 1000 steps. Training is conducted on the REDS dataset [5], augmented with synthetic UAV drift, pedestrian overlays (from MOT20), and motion blur transformations. We use the AdamW optimizer (lr=2e-4), cosine annealing, and a composite loss (MSE + LPIPS + detection loss), training for 200 epochs on two NVIDIA RTX 4070Ti GPUs. Our method outperforms baselines like DeblurGAN and Restormer, achieving 27.8 dB PSNR, 0.82 SSIM, and boosting YOLOv11 detection accuracy from 72.3% (blurred) to 89.4% (deblurred), demonstrating strong generalization in dynamic UAV scenarios.

IV. Conclusion and Future work

In this paper, we proposed a diffusion-based deblurring framework tailored for high-mobility UAV systems, effectively addressing dual-motion blur caused by simultaneous UAV and target movement. Our model demonstrated superior restoration quality and significantly improved object detection performance on REDS-based evaluations. Future work will explore real-time deployment on edge devices, integration with onboard UAV navigation systems, and training on real-world UAV flight data with multimodal sensory inputs such as LiDAR and inertial measurements for improved generalization.

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