Adaptive Data Transport Mechanism for UAV Surveillance Missions in Lossy Environments

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***Abstract*—Unmanned Aerial Vehicles (UAVs) play an increasingly critical role in Intelligence, Surveillance, and Reconnaissance (ISR) missions such as border patrolling and criminal detection due to their ability to access remote areas and transmit real-time imagery to servers. However, UAVs face limitations in payload, power, and communication bandwidth, necessitating selective data transmission strategies. While traditional methods strive to preserve maximal information in transferred video frames, missing the fact that only certain parts of images/video frames are relevant for Object Detection and Tracking (OD/OT) in ISR missions. This paper adopts a different perspective and offers an alternative AI-driven scheduling policy that prioritizes selecting regions of the image that significantly contribute to the mission objective. The key idea is tiling the image into small patches and developing a Deep Reinforcement Learning (DRL) framework that assigns higher transmission probabilities to patches that present higher overlaps with the detected object of interest while penalizing sharp transitions over consecutive frames to promote smooth scheduling shifts. Although we used YOLOv8 object detection and UDP transmission protocols as a benchmark testing scenario, the idea is general and applicable to different transmission protocols and OD/OT methods. To further boost the system's performance and avoid OD errors for cluttered image patches, we integrate it with inter-frame interpolations. With this method, we achieved about 45% improvement in terms of OD accuracy for the proposed method (F1 score:98%) compared to random selection (F1 score: 53%) when the transmission budget is 50% (we afford sending half of the image patches). Under an extremely constrained transmission budget (5%), this gain can be as high as 87%. The only cost for such improvement is a feedback channel from the ground server to drones.**

***Index Terms*—Unmanned Aerial Vehicles (UAVs), Object Detection (OD), Selective Transmission, Deep Reinforcement Learning (DRL), AI-based Networking**

I. Introduction

Unmanned Aerial Vehicles (UAVs) have evolved as critical components of modern cyber-physical systems, notably for providing Intelligence, Surveillance, and Reconnaissance (ISR) services. Their capability to access remote areas and continuously monitor without human risk has led to widespread use in applications such as disaster management, border security, environmental monitoring, and search and rescue [1]. However, due to payload and power constraints, UAVs are resource-limited [2]. UAVs transform ISR data into real-time intelligence, leveraging advanced sensors for critical data collection to enhance decision-making and mission success.

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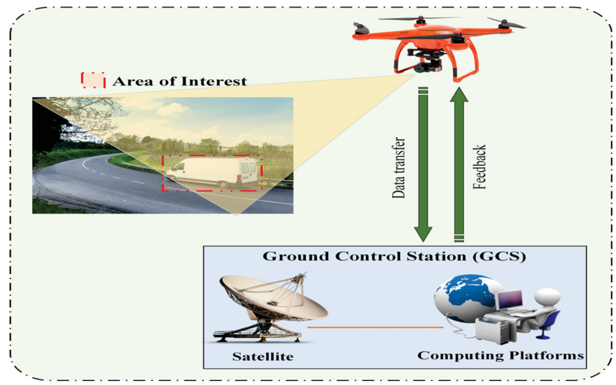

Fig. 1. Overview of the UAV-based surveillance system with a feedback loop between the UAV and GCS for real-time object detection and monitoring.

UAVs primarily provide ISR services through video streaming, crucial for real-time decision-making. Standard video compression methods such as HEVC, H.264/AVC, and VVC effectively reduce transmission bitrates by leveraging spatial and temporal correlations within frames, minimizing quality loss during data reduction [3]. Techniques such as block-based motion correction in H.264/AVC, enhanced block sizes in HEVC, and VVC's bitrate savings of up to 50% over HEVC support high-resolution video transmission over bandwidth-limited networks, typical in UAV surveillance. However, these methods are less suited for ISR applications focused on specific Regions of Interest (ROI) within frames [3].

In applications like object detection and target tracking, selective transmission of relevant frame parts could optimize compression further while maintaining critical functionality. In a real-world scene, when we focus our eyes on an object, we naturally filter out irrelevant background details, which allows us to concentrate solely on the object itself. Similar to human visual focus, selective transmission reduces background interference, adapting to environmental factors such as lighting and noise. Traditional object detection, including CNN-based methods [4], often processes entire images equally, which may reduce accuracy due to noise from irrelevant regions, making the system sensitive to visual variations in the background.

Manual or rule-based selection of image regions is often inflexible and inefficient, particularly in dynamic ISR environments. As a result, there has been a growing shift toward using Reinforcement Learning (RL) approaches, which enable more efficient and autonomous selection by continuously adapting to mission requirements in real time.

Several studies have explored the application of RL to enhance object detection by refining the selection and processing of image regions. A notable example is the integration of RL with region selection and bounding box refinement networks, aimed at optimizing detection accuracy by refining region proposals and improving feature integration [5]. This method focuses on optimizing detection accuracy within computational constraints. Uzkent et al. [6] use RL to optimize object detection over large images by selectively changing the spatial resolution in different image regions to reduce processing time while maintaining accuracy. In contrast, our research emphasizes object detection with minimal data, selectively transmitting and processing only critical image segments, which is essential for resource-constrained UAV ISR missions.

In our work, we propose an adaptive communication protocol that combines the speed of User Datagram Protocol (UDP) with mechanisms to ensure that critical video data is transmitted efficiently and reliably during real-time UAV ISR missions. We leverage RL to automatically select key areas of the video frame and integrate the YOLOv8 [7] object detection algorithm to prioritize the most critical portions, ensuring they are sufficient for accurate object detection and tracking. Additionally, a feedback mechanism continuously refines the transmission strategy in response to real-time dynamic changes in network conditions and mission requirements, ensuring optimal performance.

The main contributions of this work include:

- Design an RL-based intra-frame scheduling policy that assigns transmission probability to image patches based on their contribution to the mission-oriented objective. This method is integrable with optimized compression and scheduling methods to optimize resource utilization for resource-constrained UAVs.
- Implement an object detection that integrates inter-frame interpolation and YOLOv8 for accelerated performance.
- Incorporating a penalization term into the RL objective function to penalize sharp transitions to avoid abrupt policy shifts between consecutive frames.

II. System Model

A. Network Architecture and Real-Time Data Transmission

The proposed system is designed to enhance UAV-based surveillance missions by optimizing the transmission of real-time video data. A UAV captures real-time video data and transmits it frame by frame to the Ground Control Station (GCS) after some preprocessing. $F^{(n)}$ represents the n-th frame captured by the UAV, where each frame is divided into a grid of $K \times K$ image patches, denoted as $S_{i\times j}^{(n)}$ for $i, j = 1, 2, \ldots, K$.

It uses a UDP [8] protocol to ensure low-latency communication, which is critical for real-time applications. In the proposed scheme, each patch $S_{i\times j}^{(n)}$ is transmitted as an independent packet, and the packet header includes all necessary information to reconstruct the frame $F^{(n)}$ at the GCS. The transmission probability $P_{i\times j}^{(n)}$, determined by the policy Π, dictates which patches are transmitted based on their importance. This selective transmission reduces bandwidth usage and increases transmission efficiency. Fig. 1 illustrates a UAV-based surveillance system where the UAV continuously monitors an area of interest and communicates with the GCS through a feedback loop, enabling real-time analysis and decision-making based on detected objects.

Upon receiving the packets, the GCS reassembles the frame $F^{(n)}$ from the received patches. If some patches are lost, the corresponding cells in the frame are initially replaced with black filler sections, which are later replaced by interpolated estimates of the patch. This step ensures that the reconstructed image is smooth and visually coherent, enhancing the quality of the data used for further analysis.

B. Deep Q-Network for Object Detection and Trajectory Prediction

Upon receiving video frames, the Ground Control Station (GCS) uses a Deep Q-Network (DQN) combined with YOLOv8 for object recognition. The DQN is a reinforcement learning model designed to optimize sequential decision-making, which is crucial in dynamic and time-sensitive surveillance scenarios. Basically, YOLOv8 identifies and classifies items within grid cells, outputting bounding boxes to emphasize areas of interest, while the DQN leverages this information to predict trajectories, tracking object movement across frames, which is crucial for situational awareness in dynamic environments. The DQN assigns a Q-value $Q(s_i^{(n)}, a_i^{(n)})$ for cell i in frame $F^{(n)}$, representing the importance of the data contained within that cell. Cells that are determined to be more critical—such as those containing key objects or predicted movement paths—are assigned higher weights w_i. The Q-value is calculated for cell i in frame $F^{(n)}$ using the Bellman equation:

$$Q(s_i^{(n)}, a_i^{(n)}) = r_i^{(n)} + \gamma Q'(s_{i+1}^{(n)}, a_{i+1}^{(n)}) \tag{1}$$

where $r_i^{(n)}$ is the reward obtained by taking action $a_i^{(n)}$ in state $s_i^{(n)}$, $s_{i+1}^{(n)}$ represents the next state, and $a_{i+1}^{(n)}$ denotes possible actions in the next state. The reward function is designed to prioritize cells containing critical objects or significant motion. Also, γ is the discount factor, which balances the importance of immediate rewards versus future rewards [9].

The training of the DQN in our system is driven by a total loss function that combines two essential components: the Bellman error and a regularization term. The Bellman error, the primary loss component, is computed as the Mean Squared Error (MSE) between the predicted Q-values ($Q(s_i^{(n)}, a_i^{(n)})$) and the target Q-values. The target Q-value is calculated using the Bellman equation, where the immediate reward $r_i^{(n)}$ is added to the discounted maximum expected future reward ($\gamma Q'(s_{i+1}^{(n+1)}, a_{i+1}^{(n+1)})$) in the subsequent frame $F^{(n+1)}$. This term encourages the DQN to approximate the optimal action-value function by minimizing the difference between the current Q-values and the target Q-values. In addition to the Bellman error, the loss function includes a regularization term that penalizes significant changes in the action probabilities over consecutive time steps. This regularization is critical for maintaining stability in the learning process, as it discourages abrupt shifts in the policy that could lead to erratic behavior. The parameter λ controls the balance between accuracy and smooth transitions in the policy. The total loss function is therefore expressed as:

$$\begin{aligned}\text{Total Loss} = \frac{1}{N}\sum_{n=1}^{N}\sum_{i=1}^{M}\Big(Q(s_i^{(n)}, a_i^{(n)}) \\ - (r_i^{(n)} + \gamma Q'(s_{i+1}^{(n+1)}, a_{i+1}^{(n+1)}))\Big)^2 \\ + \lambda \sum_{n=2}^{N}\sum_{j=1}^{|A|}\left(P_j^{(n)} - P_j^{(n-1)}\right)^2\end{aligned} \tag{2}$$

where N is the frame count, and M the cell count per frame. Once the Q-values are calculated, the system assigns weights w_i to each selected cell $\hat{S}_{i\times j}^{(n)}$ in the grid. The weight for cell $\hat{S}_{i\times j}^{(n)}$ can be represented as:

$$w_i = \frac{Q(s_i, a_i)}{\sum_{j=1}^{K^2} Q(s_j, a_j)} \tag{3}$$

This normalization ensures that the weights are proportional to the relative importance of each cell, with higher weights indicating cells that are more critical for transmission.

C. Feedback Loop and Adaptive Transmission

The feedback loop enhances data transmission by updating the UAV's strategy based on DQN-assigned weights w_i. Using this feedback, the UAV prioritizes cells for the next transmission cycle, focusing on those most critical for the GCS. The transmission probability P_i for each cell can be defined as:

$$P_i = \frac{w_i}{\sum_{j=1}^{K^2} w_j} \tag{4}$$

This probabilistic approach ensures that the transmission strategy is adaptive and focused on the most important data. The feedback loop is continually refined as the DQN learns, adjusting strategies based on transmission success rates and detection consistency.

III. Experiment Results

A. Training Phase

The AU-AIR dataset is designed for aerial object detection and contains over 32,000 high-resolution, annotated video frames from UAVs, capturing vehicles, pedestrians, cyclists, and traffic signs in real-world settings [10]. It supports research in computer vision and autonomous systems, focusing on UAV applications.

In the initial setup, the UAV transmits the first four complete frames to the server using UDP. These frames initiate the training of a DQN paired with YOLOv8, which detects and identifies target objects in the frames. With Single Object Tracking (SOT) as the primary focus, the DQN utilizes received frames to learn the significance of various regions, producing a probability distribution across grid cells.

The binary mask, generated from the DQN's probabilities, identifies the most critical cells within each frame, ensuring that only essential regions are selected for transmission to optimize bandwidth. This mask is then sent back to the UAV as feedback. In each consecutive frame, the UAV divides the image into $K \times K$ (K=8) cells and applies the mask to decide the number of cells to send to the server. The selection process is based on varying percentages (5%, 10%, 25%, 50%, 75%, and 85%) of the total cells, prioritizing those with the highest probabilities to adjust data prioritization according to bandwidth constraints. The selected cells, $\hat{S}_{i\times j}^{(n)}$, in a single frame for detecting the target truck.

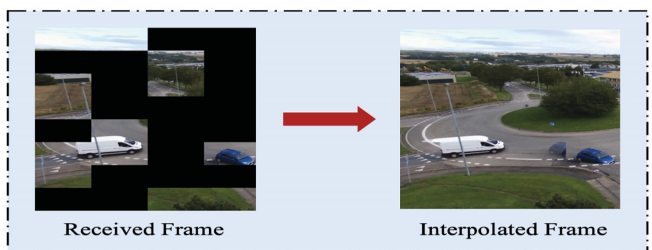

Fig. 2. Illustration of the frame reconstruction process: the received frame, containing only selectively transmitted cells, is shown on the left. The right image demonstrates the result after applying interpolation to the missing areas, effectively reconstructing a more coherent and visually complete frame.

Upon receiving the selected cells, the server reconstructs the image with placeholders for missing cells, then applies interpolation to improve visual quality, as shown in Fig. 2. The black placeholders indicate the missing cells, while the smooth transitions highlight the effectiveness of the interpolation method. The DQN and the mask are continually updated in this process, since new frames are added to the processing queue; hence, the system allows a constant updating of which parts of the image become the most important.

B. Evaluation and Performance Analysis

A key advantage of the proposed system is its reliable object detection and tracking with minimal data transmission. In this regard, we tested detection performance across selective section rates from 5% to 85% of grid cells, focusing on cells with the highest probability scores. Object detection was evaluated at each rate using the F1 score. As shown in Fig. 3, the DQN-based strategy, especially with interpolation, maintains high accuracy even at low transmission rates, down to 5% of grid cells.

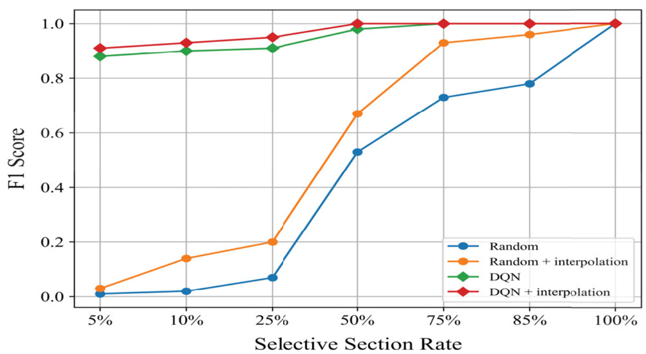

Fig. 3. Comparison of F1 scores across different transmission rates.

This capability to detect and track objects with minimal data significantly reduces bandwidth requirements, enhancing the efficiency and practicality of the proposed method for real-time UAV surveillance in bandwidth-limited environments, as shown in Fig. 4. Additionally, Fig. 5 displays the transmitted data sizes at various selective section rates, underscoring the method's effectiveness in conserving bandwidth while maintaining reliable object detection.

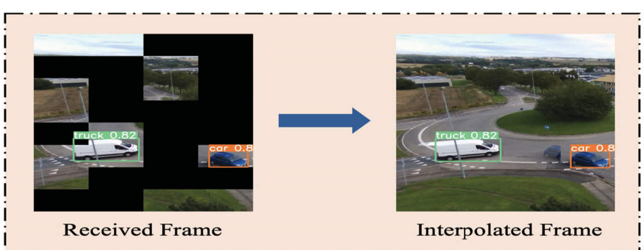

Fig. 4. Object detection results on both the received frame and the interpolated frame.

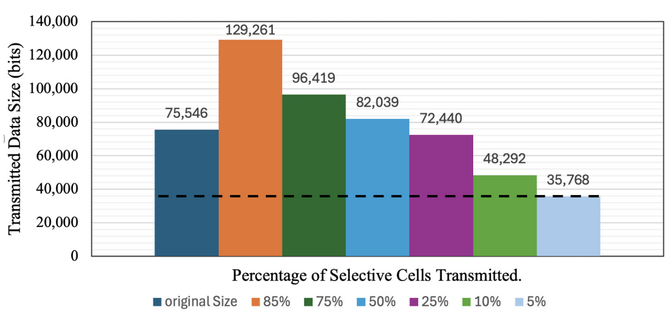

Fig. 5. Comparison of Transmitted Data Size (bits) between sending the entire image and independently sending split cells at varying percentages.

IV. Conclusion

This work presents a DQN-based selective transmission approach to enhance object detection and tracking for real-time UAV surveillance. Traditional methods focus on optimizing video compression and transmission to stream entire frames under resource constraints. In contrast, our approach prioritizes transmitting only essential image regions that contribute directly to mission objectives. Incorporating interpolation further improves object recognition quality with minimal data. The results obtained from experiments illustrate that the proposed approach yields dependable performance in constrained communication environments. The gain in object detection and tracking accuracy is about 45% with respect to random selection when the transmission budget is 50% (F1 score). This gain can be as high as 90% for an extremely constrained transmission budget (5%). This is achieved with minimal processing delay and a lightweight feedback channel, supporting real-time streaming at 30 FPS. These findings confirm the system's utility in constrained communication environments. Future enhancements could integrate this method with modern video coding and compression for greater transmission efficiency. Extending Multi-Object Tracking (MOT) capabilities would also increase the system's effectiveness in complex, multi-target surveillance scenarios.

References

[1] S. P. H. Boroujeni and A. Razi, "Ic-gan: An improved conditional generative adversarial network for rgb-to-ir image translation with applications to forest fire monitoring," *Expert Systems with Applications*, vol. 238, p. 121962, 2024.

[2] S. P. H. Boroujeni, A. Razi, S. Khoshdel, F. Afghah, J. L. Coen, L. O'Neill, P. Fule, A. Watts, N.-M. T. Kokolakis, and K. G. Vamvoudakis, "A comprehensive survey of research towards ai-enabled unmanned aerial systems in pre-, active-, and post-wildfire management," *Information Fusion*, p. 102369, 2024.

[3] D. Ammous, F. Kammoun, and N. Masmoudi, "Survey on video streaming for uav," in *2023 IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*, pp. 01–06, IEEE, 2023.

[4] R. L. Galvez, A. A. Bandala, E. P. Dadios, R. R. P. Vicerra, and J. M. Z. Maningo, "Object detection using convolutional neural networks," in *TENCON 2018-2018 IEEE region 10 conference*, pp. 2023–2027, IEEE, 2018.

[5] M. Zhou, R. Wang, C. Xie, L. Liu, R. Li, F. Wang, and D. Li, "Reinforcenet: A reinforcement learning embedded object detection framework with region selection network," *Neurocomputing*, vol. 443, pp. 369–379, 2021.

[6] B. Uzkent, C. Yeh, and S. Ermon, "Efficient object detection in large images using deep reinforcement learning," in *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 1824–1833, 2020.

[7] H. Lou, X. Duan, J. Guo, H. Liu, J. Gu, L. Bi, and H. Chen, "Dc-yolov8: small-size object detection algorithm based on camera sensor," *Electronics*, vol. 12, no. 10, p. 2323, 2023.

[8] S. Kim, S. Shin, and J. Moon, "Udp-based extremely low latency streaming," in *2022 IEEE 19th Annual Consumer Communications & Networking Conference (CCNC)*, pp. 94–99, IEEE, 2022.

[9] M. N. Al-Hamadani, M. A. Fadhel, L. Alzubaidi, and B. Harangi, "Reinforcement learning algorithms and applications in healthcare and robotics: A comprehensive and systematic review," *Sensors*, vol. 24, no. 8, p. 2461, 2024.

[10] I. Bozcan and E. Kayacan, "Au-air: A multi-modal unmanned aerial vehicle dataset for low altitude traffic surveillance," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 8504–8510, IEEE, 2020.