Uncertainty-Aware Adaptive Huber-Loss Federated Distillation for Thermal Anomaly Detection in UAV Networks

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Thermal anomaly detection from unmanned aerial vehicles (UAVs) is increasingly used for applications such as early wildfire discovery, post-disaster monitoring, and infrastructure inspection. In practice, UAV fleets observe highly heterogeneous environments and acquire thermal imagery with variable quality caused by motion blur, sensor drift, altitude changes, and reflections. These factors yield strongly non-IID client data and heavy-tailed prediction residuals that can destabilize collaborative learning. To address these challenges under bandwidth constraints, we propose an uncertainty-aware federated distillation (FD) framework that exchanges compact logits rather than full model parameters. The framework targets binary anomaly detection and naturally extends to multi-task thermal characterization (e.g., anomaly size and growth severity) via additional heads. Our approach introduces (i) a client-adaptive Huber threshold that is learned locally to robustify distillation against outlier residuals, and (ii) heteroscedastic uncertainty weighting that down-weights ambiguous or corrupted thermal frames during local optimization. We provide an end-to-end training protocol for UAV networks and evaluate it using non-IID simulations as well as a real-world UAV case study pipeline based on a DJI Mavic platform paired with a lightweight thermal sensing payload. Finally, we perform ablation studies to isolate the contributions of adaptive robustness and uncertainty weighting under connectivity and distribution shift. Index Terms—UAV networks, thermal anomaly detection, federated learning, federated distillation, robust loss, Huber loss, uncertainty modeling, non-IID learning.

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