

## I. Related Work

### A. Small Object Detection and Resolution Limits

The fundamental bottleneck in small object detection is the scarcity of distinguishing features. When a target occupies fewer than  $15 \times 15$  pixels, class-defining details are often lost entirely [1]. Classical solutions involving super-resolution (SR) attempt to reconstruct this lost detail [2].

However, reliance on SR for scientific data collection is flawed for two reasons: correctness and latency. First, SR is fundamentally generative; it estimates high-frequency details based on learned priors, creating a risk of hallucination where the model reinforces its own biases [5]. Second, the latency advantage of SR is negligible for high-quality restoration. While lightweight models run in  $< 30\text{ms}$  on edge accelerators (e.g., Jetson Orin), high-fidelity generative models required for scientific validity often require  $> 300\text{ms}$  per frame [18]. This exceeds the mechanical slew-and-settle time of our system ( $\approx 150\text{ms}$ ), which is competitive with high-end commercial PTZ units (typically  $60\text{--}200\text{ ms}$  command latency [16]). Our system therefore chooses the mechanical penalty to obtain optical ground truth rather than the computational penalty for potentially hallucinatory estimation.

### B. Active Acquisition vs. Continuous Tracking

Most PTZ tracking literature focuses on the control problem of keeping a target centered in the frame [7, 8]. This requires mitigating total system latency (video encoding + network + mechanical response), which for IP-based systems frequently ranges from  $200\text{--}500\text{ ms}$  [17]. Our work addresses a distinct problem: *active acquisition*, or "slew-to-classification." Unlike continuous tracking, where the objective is persistence, our objective is information gain via discrete spot-checks.

Existing active perception systems like VIGIA-E [11] typically optimize for broad area coverage or anomaly detection. In contrast, our system functions as a sparse query mechanism. It identifies specific low-confidence candidates in the wide field and commits the PTZ resource to verifying them individually. This shifts the challenge from long-term stabilization to rapid, precise separate-and-verify maneuvers.

### C. Sensor-Driven Labeling

Reducing manual annotation is a central goal of both semi-supervised learning and active learning. Pseudo-labeling methods such as ASTOD [12] attempt to retrain models using high-confidence predictions, but this approach often fails in the small-object regime where the detector is consistently uncertain [13]. Similarly, active learning strategies like PPAL [15] identify informative samples but still require a human loop [14].

Our proposed "Active Acquisition" creates a fully automated hybrid. We use the selection logic of active learning (targeting less confident samples) but satisfy the label query using the PTZ sensor instead of a human. The success of this automated verification relies on the domain shift provided by optical zoom: while the target is ambiguous at  $15 \times 15$  pixels, the zoomed view restores it to a regime (e.g.,  $> 100 \times 100$  pixels) where off-the-shelf detectors already achieve near-perfect accuracy [6]. By physically bridging the gap between the surveillance view and the high-resolution training distribution of standard models, we convert a difficult "small object" inference problem into a trivial classification task, enabling the generation of verified ground-truth labels at scale.

## References

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