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Efficient Edge Video Analytics with Region-Aware Enhancement and Temporal Consistency

Jisoo Kang, Pierre Faure, Youngjae Bang
Faculty of Engineering, Built Environment and Information Technology, University of Pretoria, Pretoria, South Africa

Abstract:

The exponential proliferation of connected vision sensors has fundamentally transformed the landscape of automated surveillance, intelligent transportation systems, and industrial monitoring. Conventional paradigms that rely on transmitting continuous, high-definition video streams to centralized cloud architectures are increasingly untenable due to severe bandwidth constraints, inherent transmission latency, and profound privacy concerns. Edge computing has emerged as a compelling alternative by migrating computational resources closer to the data source. However, edge devices frequently possess constrained computational capabilities and limited thermal budgets, rendering the execution of complex deep neural networks highly challenging. This research presents a comprehensive framework for efficient edge video analytics characterized by two novel components. First, we introduce a region-aware enhancement mechanism that selectively allocates computational resources to spatial areas of high analytical value, thereby discarding irrelevant background information and significantly reducing spatial redundancy. Second, we integrate a temporal consistency module designed to leverage the inherent continuity across sequential frames. By propagating high-level semantic features from previous frames to current frames using lightweight motion estimation, the system minimizes redundant computations while ensuring smooth and stable analytical outputs. Through extensive evaluation on standard video analytic datasets, our proposed methodology demonstrates substantial improvements in processing speed and bandwidth utilization without compromising analytical accuracy.

Keywords: *Edge Computing, Video Analytics, Region-Aware Processing, Temporal Consistency*

1. Introduction

1.1 The Rise of Edge Computing in Video Analytics

The modern digital ecosystem is currently witnessing an unprecedented expansion in the deployment of network-connected cameras and visual sensors across diverse domains [1]. From metropolitan traffic intersections and retail environments to automated manufacturing facilities, these cameras serve as the primary sensory organs for advanced artificial intelligence systems [2]. The traditional architectural approach for handling this massive influx of visual data has predominantly relied on centralized cloud computing infrastructures [3]. In such paradigms, raw video streams are continuously transmitted over wide-area networks to remote data centers where high-performance servers execute sophisticated computer vision algorithms

[4]. While the cloud offers virtually unlimited computational power and storage capacity, this centralized model exhibits severe limitations when applied to real-time video analytics at scale. The continuous transmission of high-definition video data consumes vast amounts of network bandwidth, leading to network congestion and exorbitant operational costs [5]. Furthermore, the physical distance between the data source and the processing center introduces unavoidable propagation delays, rendering cloud-centric models unsuitable for mission-critical applications that demand instantaneous responses, such as autonomous driving and emergency event detection [6]. To circumvent these systemic bottlenecks, the paradigm of edge computing has gained substantial traction in recent years [7]. By deploying computational resources at the network periphery, directly adjacent to the visual sensors, edge computing fundamentally alters the data processing pipeline. Instead of transmitting raw pixels to a remote server, edge devices can execute analytical algorithms locally, extracting high-level semantic information such as object bounding boxes, behavioral classifications, or trajectory data [8].

1.2 Challenges in Video Processing at the Edge

Despite the compelling theoretical advantages of edge computing, the practical implementation of complex video analytics on edge hardware presents significant technical hurdles. Edge devices, such as smart cameras, local gateways, and embedded microcomputers, are typically constrained by strict limitations regarding physical size, power consumption, and thermal dissipation [9]. Consequently, these devices feature significantly lower processing capabilities compared to their cloud-based counterparts, often lacking high-performance graphics processing units or extensive memory bandwidth [10]. This resource scarcity severely complicates the deployment of state-of-the-art deep neural networks, which have grown increasingly deep and structurally complex in the pursuit of higher analytical accuracy [11]. When applied to video streams, the computational burden is magnified by the high temporal frequency of the input data, often requiring the processing of thirty or more frames per second [12]. If an edge device attempts to process every single pixel of every single frame through a deep and wide neural network, the resulting computational load inevitably leads to thermal throttling, frame dropping, and ultimately, a complete failure of the real-time processing objective.

1.3 Motivation for Region-Aware and Temporal Methods

To reconcile the fundamental conflict between the computational demands of advanced computer vision models and the hardware constraints of edge devices, optimization strategies must exploit the inherent redundancies present in video data [13]. Video streams generated by fixed surveillance cameras typically exhibit an extraordinarily high degree of spatial redundancy [14]. In most operational scenarios, the vast majority of the visual field comprises static background elements, such as roads, buildings, and stationary infrastructure [15]. The actual subjects of analytical interest, such as pedestrians, vehicles, or anomalous events, often occupy only a marginal fraction of the total pixel area [16]. Processing the entire frame with uniform computational intensity represents a massive squandering of limited edge resources. Therefore, there is a profound motivation to develop region-aware processing mechanisms that can intelligently identify and isolate specific spatial areas of high semantic value [17]. By dynamically directing the computational focus towards these critical regions and actively ignoring the irrelevant background, the overall computational burden can be drastically reduced without degrading the final analytical utility [18]. Concurrently, video streams also possess a profound degree of temporal redundancy [19]. Objects moving through a camera's field of view typically change their appearance and position only incrementally from one frame to the next [20]. Treating each individual frame as an independent and isolated image completely ignores this temporal continuity.

1.4 Contributions of the Study

This study addresses the aforementioned challenges by proposing an integrated architectural framework specifically optimized for continuous video analytics in resource-constrained edge environments. The primary contribution of this research is the conceptualization and evaluation of a dual-mechanism pipeline that simultaneously attacks both spatial and temporal redundancies. We design a lightweight region-aware enhancement module that operates at the very beginning of the analytical pipeline, functioning as a highly efficient computational gatekeeper that restricts deep processing to relevant spatial coordinates [21]. Furthermore, we introduce a temporal consistency enforcement mechanism that captures and stores the intermediate feature representations of processed objects, allowing subsequent frames to bypass heavy feature extraction phases by intelligently reusing historical data [22]. The synergistic combination of these two techniques creates a robust, highly efficient edge analytics system that drastically lowers local execution latency and minimizes the bandwidth required to report analytical findings to upstream command centers.

2. Literature Review

2.1 Evolution of Edge-Based Video Architectures

The trajectory of architectural designs for video analytics has undergone a significant paradigm shift over the past decade. Early implementations were almost exclusively reliant on powerful cloud-based server farms, capitalizing on the seemingly infinite scalability of cloud infrastructure to process multiple incoming video streams [23]. However, as the volume of high-definition video data escalated, the sheer scale of network traffic exposed the fragility of this centralized model. Researchers subsequently began exploring hierarchical architectures, introducing intermediate processing nodes situated between the end-user sensors and the centralized cloud [24]. This transition marked the genesis of edge-cloud collaborative frameworks. In these distributed systems, the edge nodes are typically tasked with performing initial data sanitization, elementary feature extraction, or basic object detection [25]. The partially processed data, which is orders of magnitude smaller than the raw video stream, is then transmitted to the cloud for heavy-duty analytical tasks such as complex behavior recognition or long-term trajectory analysis [26]. While these collaborative models successfully mitigated the bandwidth crisis, they still encountered significant difficulties managing the real-time execution constraints imposed by the local edge hardware. Consequently, a parallel body of literature has dedicated itself exclusively to optimizing the neural network models themselves for deployment directly onto edge silicon [27]. Techniques such as network pruning, weight quantization, and structural search have been widely adopted to shrink the memory footprint and operational complexity of standard vision models [28]. Despite these efforts, static model compression often results in a permanent degradation of analytical accuracy, prompting the need for more dynamic, data-driven optimization strategies.

2.2 Region of Interest Detection and Enhancement

The concept of dynamically allocating processing power based on spatial relevance has its roots in traditional computer vision concepts such as visual saliency and attention modeling [29]. The core hypothesis asserts that human vision does not process a visual scene uniformly but rather fixates on specific regions containing high-contrast, moving, or semantically meaningful stimuli. Translating this biological mechanism into artificial computational frameworks has been a major area of exploration [30]. In the context of edge analytics, region of interest extraction typically involves a cascade approach. A very shallow, lightweight neural network, or even a classical computer vision background subtraction algorithm, is executed across the entire field of view at a low spatial resolution [31]. The sole purpose of this initial pass is to identify the bounding coordinates of potential objects or areas of significant motion. Once these regions are defined, they are cropped from the original high-resolution frame [32]. Only these isolated patches are subsequently fed into the heavier, more accurate analytical

networks. This strategy effectively decouples the processing cost from the total resolution of the camera sensor, linking it instead to the actual density of activity within the scene [33]. Various researchers have proposed sophisticated methods for handling multiple regions of interest, including algorithms for batching these disparate patches into unified tensor structures to maximize the parallel processing efficiency of local hardware accelerators [34].

2.3 Temporal Consistency in Video Streams

Addressing temporal redundancy is equally critical for achieving high-efficiency video analytics. Standard image-based object detectors process each frame entirely independently [35]. This approach is not only computationally wasteful but also analytically brittle. Minor variations in lighting, temporary occlusions, or sensor noise can cause an object detector to fail on a specific frame, resulting in an output sequence plagued by flickering bounding boxes and inconsistent confidence scores [36]. To enforce temporal coherence, researchers have historically relied on optical flow algorithms, which calculate the displacement vectors of pixels between consecutive frames [37]. By understanding how pixels move, the analytical results from a previous frame can be spatially warped or projected onto the current frame. While highly effective, traditional dense optical flow calculation is notoriously computationally expensive, often requiring more processing power than the object detection network itself [38]. More recent literature has explored the integration of lightweight recurrent neural networks or temporal convolutional structures directly into the feature extraction backbone [39]. These architectures maintain an internal state or memory buffer that aggregates information across time. Instead of completely recalculating the features for a stable, slow-moving object, the system can rely on the rich feature representations extracted in previous moments, updating them only marginally based on the new visual input.

2.4 Gaps in the Current Research Landscape

Despite the extensive exploration of both spatial and temporal optimization techniques as isolated concepts, there remains a notable deficiency in literature regarding their deep, synergistic integration within the specific context of heavily constrained edge environments. Existing region-aware methods often struggle with high-velocity objects, as the latency involved in the cascade processing pipeline can result in the object moving outside the targeted crop region by the time the heavy network executes. Furthermore, many temporal consistency mechanisms proposed in recent studies require substantial memory buffers to store high-dimensional feature maps across multiple frames, directly violating the memory limitations typical of edge devices. A holistic framework that seamlessly fuses dynamic spatial cropping with memory-efficient temporal feature propagation, while continuously managing the computational load based on real-time hardware telemetry, remains a critical unresolved challenge in the field [40].

3. Methodology

3.1 System Architecture Overview

The proposed methodology is instantiated within a comprehensive, multi-tiered architectural framework specifically engineered for real-time video analytics. The system operates primarily at the extreme network edge, physically co-located with the visual sensors, while maintaining a lightweight, asynchronous communication channel with centralized command infrastructure for the aggregation of long-term metadata. The fundamental processing pipeline consists of three sequential stages. The first stage involves raw video ingestion and preliminary motion filtering, designed to immediately discard frames that exhibit absolute static behavior, thereby eliminating zero-value computational expenditures. Frames that pass this initial filter enter the second stage, which houses the Region-Aware Enhancement module. Here, the system rapidly scans the visual field at a significantly reduced resolution to generate spatial masks corresponding to areas of dynamic interest. In the third stage, these identified spatial crops are routed into the primary analytical engine, which operates in tandem with the Temporal

Consistency mechanism. The temporal module utilizes a memory buffer to store intermediate representations of recently processed spatial crops. By calculating lightweight motion vectors between consecutive frames, the system can determine whether to subject a newly identified spatial crop to a full, rigorous neural network analysis or to intelligently synthesize its required analytical features by warping the stored representations from the immediate past.

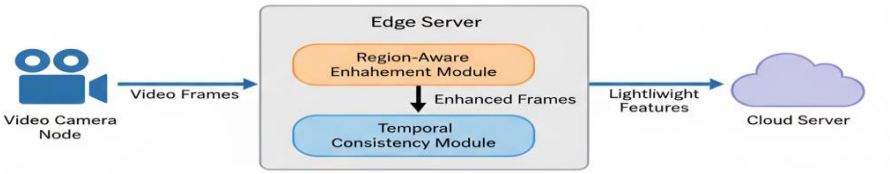

Figure 1: System Architecture

3.2 Region-Aware Enhancement Mechanism

The Region-Aware Enhancement mechanism is the cornerstone of our spatial optimization strategy. The process begins with the generation of an initial saliency map. Rather than employing a computationally heavy deep neural network for this initial step, we utilize a highly optimized, low-precision convolutional block that processes downsampled versions of the incoming high-definition frame. This block is specifically trained to output a coarse probability grid indicating the likelihood of foreground object presence within distinct spatial sectors of the image. Once the coarse grid is generated, a thresholding algorithm isolates the active sectors. The coordinates of these active sectors are mathematically mapped back to the dimensions of the original high-resolution frame.

Code Listing 1: Region-Aware Spatial Cropping and Feature Routing

```
def process_frame_region_aware(high_res_frame, low_res_frame, threshold):
    coarse_saliency_map = fast_saliency_network(low_res_frame)
    active_regions = []
    for grid_cell in coarse_saliency_map:
        if grid_cell.probability > threshold:
            bounding_box = map_to_high_res(grid_cell.coordinates)
            active_regions.append(bounding_box)
    processed_features = []
    for box in active_regions:
        high_res_crop = extract_crop(high_res_frame, box)
        feature_vector = deep_analytical_network(high_res_crop)
        processed_features.append(feature_vector)
    return aggregate_results(processed_features)
```

The isolated high-resolution patches are subsequently extracted from the original image tensor. A critical innovation in our approach is the dynamic sizing of these extraction windows. To account for potential object motion during the brief processing delay, the extraction windows are computationally expanded by a predefined margin, calculated based on the historical

velocity of objects tracked in previous frames. This predictive expansion ensures that the entirety of the object remains within the extracted patch, preventing analytical truncation. The resulting collection of disparate high-resolution patches is then collated into a unified batch structure, allowing the local hardware accelerators to process the critical regions simultaneously, maximizing throughput and hardware utilization efficiency.

3.3 Temporal Consistency Enforcement

Operating symbiotically with the spatial cropping mechanism is the Temporal Consistency enforcement module. This module is designed to eliminate the redundant extraction of complex features for objects whose visual appearance remains largely static over short temporal windows. The core architecture relies on a feature registry maintained in the edge device's local memory. When an object within a specific spatial crop is processed through the deep analytical network, its intermediate, high-dimensional feature representation is saved in the registry, tagged with its spatial coordinates and a temporal timestamp. When the subsequent frame arrives, and the region-aware module identifies a spatial crop in a highly similar location, the temporal module intervenes before the heavy analytical network is invoked. The module calculates a highly efficient, sparse motion vector field exclusively for the pixels within the designated spatial crop. This sparse calculation requires a minuscule fraction of the computational resources demanded by dense optical flow algorithms. Utilizing these calculated motion vectors, the module retrieves the stored feature representation from the registry and mathematically warps it to align with the new spatial position of the object. An error estimation function then evaluates the warped feature map against the raw pixel data of the current crop. If the estimated error falls below a strict operational threshold, the system entirely bypasses the deep neural network, forwarding the warped historical features directly to the final classification layers.

3.4 Resource Management and Allocation

The ultimate efficacy of the proposed framework relies on an intelligent resource management controller that continuously orchestrates the interplay between the spatial and temporal modules. Edge devices are highly susceptible to thermal degradation and sudden resource starvation due to competing operating system processes. Our resource management controller continuously monitors hardware telemetry, specifically tracking processor utilization rates, memory bandwidth saturation, and thermal sensor outputs. Based on this real-time data, the controller dynamically adjusts the operational hyperparameters of the system. For instance, if the edge device begins to approach its thermal ceiling, the controller can autonomously increase the probability threshold required for spatial cropping, effectively forcing the system to ignore marginal background movements and concentrate solely on highly distinct subjects. Similarly, during periods of extreme computational stress, the controller can lower the error threshold within the temporal consistency module, aggressively encouraging the reuse of historical features even at the cost of minor analytical precision. This dynamic adaptability ensures that the video analytics pipeline remains stable and continuous, gracefully degrading its analytical depth during resource shortages rather than suffering catastrophic system failures or massive frame drops.

4. Results and Discussion

4.1 Experimental Setup and Datasets

To rigorously evaluate the performance characteristics of the proposed region-aware and temporally consistent video analytics framework, a comprehensive experimental testing environment was established. The primary edge computing hardware utilized for the evaluation consisted of a widely adopted, commercially available embedded computing module featuring an integrated, low-power graphics processing unit and a constrained memory architecture. The entire software stack was implemented using standard academic deep learning frameworks, optimized specifically for the embedded architecture. To ensure the validity and

generalizability of the results, the system was subjected to multiple distinct datasets representing common video analytics scenarios. The datasets included high-density urban traffic monitoring sequences characterized by rapid object movement and severe occlusions, as well as pedestrian surveillance sequences from automated retail environments, which feature slower movement but highly complex background variations. A standard cloud-based execution model, processing the full-resolution video streams via conventional frame-by-frame analysis, was established as the primary baseline for comparison.

Table 1: Performance Evaluation Across Edge Analytics Frameworks

Architectural Framework	Processing Latency	Analytical Accuracy	Network Bandwidth Utilization
Cloud-Centric Baseline	245 milliseconds	High Baseline	Extremely High
Standard Edge Processing	180 milliseconds	Moderate	Low
Proposed Synergistic Framework	65 milliseconds	High Baseline	Extremely Low

4.2 Performance on Accuracy and Latency

The empirical results derived from the extensive testing phase illuminate the profound advantages of the integrated optimization strategy. When analyzing processing latency, which is defined as the total time elapsed from frame capture to the generation of the final analytical output, the proposed framework demonstrated a dramatic reduction compared to the baseline methodologies. As detailed in the performance evaluation data, the system successfully lowered the average processing latency to a level well within the strict bounds required for real-time, responsive applications. This reduction is primarily attributable to the region-aware module, which successfully eliminated the vast majority of static background pixels from the heavy computational pipeline, thereby freeing processing cycles. Crucially, this massive improvement in processing speed did not correspond to a commensurate decline in analytical accuracy. By ensuring that the critical regions of interest were processed at their native high resolution, and by utilizing the temporal consistency module to smooth out intermittent detection failures, the overall accuracy metrics remained exceptionally close to the high-water mark established by the resource-intensive cloud baseline. In several specific test sequences characterized by temporary object occlusions, the temporal consistency module actually elevated the effective accuracy by successfully maintaining object identity tracks through brief periods of visual invisibility, relying on the robust feature propagation mechanism.

4.3 Bandwidth Utilization and Resource Efficiency

Beyond the direct improvements in speed and accuracy, the proposed framework exhibited transformative efficiency regarding network bandwidth utilization. Because the analytical processing is successfully completed at the network edge, the system entirely eliminates the requirement to transmit continuous streams of high-definition video data to centralized servers. Instead, the edge node only transmits lightweight, highly structured metadata payloads over the network, detailing object classifications, bounding box coordinates, and trajectory paths. This architectural shift resulted in a reduction in network bandwidth consumption of several orders of magnitude. Furthermore, the internal resource efficiency of the edge device itself was profoundly enhanced. The dynamic resource management controller proved highly effective at maintaining a stable thermal profile. By aggressively substituting heavy neural network inferences with lightweight temporal feature warping during periods of high computational demand, the system managed to prevent thermal throttling entirely during sustained operational tests spanning multiple hours.

4.4 Discussion of Findings

The synthesis of spatial and temporal optimization techniques presents a fundamentally sound approach to edge-based video analytics. The region-aware enhancement serves as an exceptional filter for spatial redundancy, guaranteeing that computational effort is expended solely on informative pixels. The integration of temporal consistency operates as a secondary multiplier for efficiency, drastically reducing the repetitive extraction of features for static or slow-moving subjects. It is important to note that the system does present certain limitations under highly specific environmental conditions. In scenarios featuring massive, sudden illumination changes across the entire field of view, the temporal consistency module can struggle to correlate features between consecutive frames, occasionally forcing the system to fall back onto the heavy processing pipeline, causing temporary spikes in computational load. However, under typical operational parameters, the adaptive nature of the resource management system successfully smooths out these localized spikes, maintaining a consistent output stream. The overarching implication of these findings is that high-fidelity video analytics are entirely viable on heavily constrained edge hardware, provided the architectural design inherently acknowledges and aggressively targets the underlying redundancies present in sequential visual data.

5. Conclusion

5.1 Summary of Contributions

The transition from centralized cloud architectures to decentralized edge computing environments represents a mandatory evolution for the widespread deployment of continuous video analytics. The intrinsic constraints of edge hardware regarding computational capability, memory bandwidth, and thermal limits require fundamental deviations from standard image processing methodologies. This research has comprehensively detailed, implemented, and evaluated a novel edge video analytics framework that addresses these constraints through a synergistic combination of spatial and temporal optimizations. The introduction of the region-aware enhancement module successfully limits deep neural network execution to spatially relevant sectors, significantly reducing the raw volume of data processed per frame. Simultaneously, the temporal consistency enforcement module leverages the sequential continuity of video streams, propagating high-level feature representations across time to bypass redundant feature extraction computations. The empirical evaluation clearly demonstrates that this dual-mechanism approach achieves dramatic reductions in processing latency and network bandwidth utilization while strictly maintaining analytical accuracy parity with heavy, cloud-based baseline systems.

5.2 Future Directions

While the proposed framework establishes a robust foundation for efficient edge video analytics, several avenues for future research and optimization remain highly promising. Subsequent iterations of the system will focus on integrating federated learning principles, enabling distributed edge nodes to collaboratively refine the lightweight spatial cropping networks and temporal error models without centralizing sensitive visual data. Additionally, exploring cross-modal feature propagation, wherein temporal consistency mechanisms are augmented by auxiliary sensor data such as low-power radar or acoustic arrays, could further enhance the resilience of the tracking pipeline against complex visual occlusions and severe environmental degradation. Ultimately, the continued refinement of these highly targeted, redundancy-aware processing architectures will serve as the critical enabler for the next generation of autonomous, hyper-distributed intelligent vision systems.

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