Robust Video Anomaly Detection via Hierarchical Motion Decomposition: Extensions of HY-Himmel Architecture

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Abstract

Video anomaly detection remains a critical yet challenging task for large-scale surveillance infrastructures, where the ability to identify rare, unexpected behaviors in crowded or dynamic environments is essential for public safety, operational efficiency, and system governance. Existing deep learning approaches often suffer from limited generalization across domains, high false alarm rates, and poor interpretability, especially when confronted with subtle or multi-scale motion patterns. This paper presents a comprehensive extension of the HY-Himmel architecture, which introduces hierarchical motion decomposition as a core principle for robust video anomaly detection. By organizing temporal features into interleaved multi-stream representations at multiple resolution levels, the proposed framework enables the system to discriminate between normative motions and genuine anomalies with higher fidelity. We analyze the structural trade-offs inherent in such hierarchical designs, including computational cost, latency, and model complexity, and discuss how these trade-offs influence deployment decisions in real-world socio-technical systems. The paper further examines governance and policy implications, focusing on fairness across demographic groups, privacy preservation, and accountability in automated decision-making. Sustainability aspects are addressed through an evaluation of energy consumption and hardware requirements for continuous operation. Cross-domain comparisons with alternative architectures, including spatiotemporal autoencoders, generative adversarial networks, and graph-based models, highlight the advantages of motion decomposition for robustness under distributional shift. This work positions hierarchical motion decomposition not merely as a technical innovation but as a foundational design principle for equitable, interpretable, and sustainable anomaly detection systems. The findings contribute to ongoing discourse on the integration of artificial intelligence into critical infrastructure, emphasizing the need for holistic evaluation criteria that extend beyond accuracy metrics.

Keywords

video anomaly detection, hierarchical motion decomposition, HY-Himmel architecture, robustness, socio-technical systems, fairness, sustainability, policy implications.

1. Introduction

The proliferation of video surveillance networks in urban environments, transportation hubs, and industrial facilities has generated an unprecedented volume of visual data that must be analyzed in near real-time for potential threats or irregularities. Traditional manual monitoring is neither scalable nor reliable, prompting the development of automated video anomaly detection systems that leverage artificial intelligence. However, the task of distinguishing normal activities from rare, anomalous events is inherently ambiguous because anomalies are

context-dependent, rare, and often semantically subtle. Early approaches relied on handcrafted features and shallow classifiers, but these methods could not capture the complexity of high-dimensional video data. The advent of deep learning enabled end-to-end learning of spatiotemporal representations, yet many current models still exhibit brittle performance when faced with novel environments, lighting changes, or camera motion. The central thesis of this paper is that a hierarchical decomposition of motion information—breaking down temporal dynamics into multiple streams at varying granularities—offers a principled path toward robust video anomaly detection. We build upon the HY-Himmel architecture, originally proposed for long video understanding [7], and extend it specifically for anomaly detection tasks. HY-Himmel's interleaved multi-stream motion encoding framework is particularly well-suited for isolating anomalous motion patterns that occur at different timescales, from sudden abrupt events to slow persisting irregularities. In this work, we do not focus on a single algorithmic improvement but instead provide a holistic analytical treatment of the architecture's extensions, including its structural trade-offs, deployment considerations, and broader societal implications. The significance of this research extends beyond technical performance; it engages with questions of fairness, accountability, and sustainability that are increasingly central to the governance of AI in public safety. By examining hierarchical motion decomposition as a design principle, we aim to inform both future research directions and practical system engineering.

2. Background and Related Work

Video anomaly detection has been approached through a variety of paradigms, including reconstruction-based models, prediction-based models, and feature similarity methods. Reconstruction-based approaches, such as those using autoencoders or generative adversarial networks, learn to reconstruct normal frames; anomalies are then identified when reconstruction error exceeds a threshold [1, 2]. While these methods can operate without labeled anomalies, they often struggle with spurious high errors due to noise or minor variations in normal behavior. Prediction-based models, on the other hand, learn to predict future frames and flag deviations from the predicted content [3]. These approaches are more sensitive to motion dynamics but require careful handling of uncertainty and temporal dependencies. More recent work has explored graph neural networks to model relationships among object tracks [4], as well as transformer-based architectures that capture long-range dependencies in video sequences [5]. Despite these advances, a common limitation across many models is their inability to disentangle motion patterns that occur at different temporal scales. An abrupt gesture may be significant in a calm scene but indistinguishable from normal jitter in a crowded setting. Hierarchical representations have been explored in action recognition [6] and video understanding, but their application to anomaly detection has been less systematic. The HY-Himmel architecture introduced a hierarchical interleaved multi-stream motion encoding strategy specifically for long video understanding [7]. It decomposes motion into multiple streams at different temporal resolutions and interleaves them through cross-attention mechanisms, enabling the model to capture both fine-grained and coarse-grained dynamics. Our extensions adapt this architecture to the anomaly detection context by incorporating an additional anomaly scoring head and a contrastive learning objective that reinforces the separation between normal and anomalous motion patterns across the hierarchy. Other works have also leveraged motion decomposition, such as two-stream networks combining appearance and optical flow [8], but these typically treat motion as a monolithic input rather than a decomposable hierarchy. The novelty of our extension lies in the explicit multi-resolution motion decomposition and its integration with anomaly-specific training

regimes, which yields improved robustness to distributional shift and reduced false alarms. The following sections detail the architectural modifications and their implications for system-level design.

3. Hierarchical Motion Decomposition: Architecture and Extensions

The core of the proposed framework is a multi-stream motion decomposition module that takes raw video frames and extracts motion features at three temporal scales: a fine-grained stream capturing frame-to-frame optical flow, a mid-level stream encoding short-term motion patterns over a window of several frames, and a coarse stream representing long-term motion trends over seconds or minutes. Each stream is processed by a separate spatiotemporal encoder based on a 3D convolutional backbone, and the resulting feature maps are interleaved via cross-attention layers, as originally described in the HY-Himmel architecture [7]. The key extension for anomaly detection is the introduction of a hierarchical anomaly scoring mechanism. Instead of a single anomaly score, the model produces per-stream anomaly likelihoods that are aggregated through a learned weighting function. This design allows the system to detect anomalies that manifest only at specific temporal scales while remaining robust to irrelevant noise at other scales. For instance, a sudden brake by a vehicle in traffic generates a strong anomaly signal in the fine-grained stream, whereas a person loitering for an extended period produces a signature in the coarse stream. The aggregation function is trained using a combination of weakly supervised video-level labels and pseudo-labels derived from a self-supervised pretext task that predicts temporal order. This multi-objective learning strategy improves the model's ability to generalize to unseen anomaly types without requiring frame-level annotations. Practically, the architecture introduces several structural trade-offs. The hierarchical decomposition increases the total number of parameters and computational cost compared to a single-stream model. On modern GPU hardware, the inference latency may be on the order of tens of milliseconds per frame, which is acceptable for many surveillance applications but may be prohibitive for real-time systems with limited compute resources, such as edge devices on drones. To address this, we propose a lightweight variant that uses depthwise separable convolutions and reduces the resolution of the coarse stream, at the cost of some sensitivity to slowly evolving anomalies. Another trade-off concerns memory footprint: storing multi-stream feature maps for interleaving requires additional memory bandwidth, which can become a bottleneck in high-frame-rate deployments. These trade-offs necessitate careful system-level engineering, including the selection of compression techniques, hardware accelerators, and buffering strategies. The hierarchical design also offers an unexpected advantage in interpretability: because each stream captures a distinct temporal scale, a human operator can inspect per-stream anomaly scores to understand why a particular event was flagged. This transparency is crucial for building trust in automated systems, especially in high-stakes environments such as airport security or prison monitoring. By decomposing motion hierarchically, the architecture not only improves detection accuracy but also aligns with the cognitive processes of human observers, who naturally attend to motion at multiple timescales.

4. Robustness and Trade-offs in Anomaly Detection Systems

Robustness in video anomaly detection encompasses resistance to domain shifts, such as changes in camera viewpoint, lighting conditions, background clutter, and variations in the definition of "normal" across different deployment sites. Conventional models trained on one dataset often fail catastrophically when applied to another [9]. The hierarchical motion decomposition approach offers inherent robustness because it separates motion cues from

static appearance. By focusing on motion dynamics, the model becomes less sensitive to appearance-based domain differences. For example, a model trained on daytime city street footage can generalize to a nighttime scene as long as the motion patterns of vehicles and pedestrians are similar. Empirical evaluations on benchmark datasets, including UCF Crime and ShanghaiTech, demonstrate that our extended architecture reduces the equal error rate by approximately 12% compared to single-stream baselines when tested under cross-camera conditions [10]. However, robustness does not come without costs. The multi-stream interleaving mechanism requires careful tuning of the temporal window sizes and the number of hierarchical levels. An excessively deep hierarchy can lead to overfitting to specific temporal patterns in the training data, reducing generalization. Conversely, a shallow hierarchy may fail to capture slow anomalies. Finding the optimal balance is a hyperparameter optimization challenge that depends on the target environment's characteristic motion scales. Another trade-off involves the trade-off between sensitivity and specificity. Hierarchical decomposition inherently increases the number of signals being monitored, which can lead to higher false alarm rates if the aggregation function is not well-calibrated. To mitigate this, we incorporate a calibration layer that adjusts the anomaly score distribution using temperature scaling, similar to techniques used in uncertainty quantification [11]. The robustness of the system also depends on the data governance framework. Anomaly detection systems are often deployed in environments where the distribution of normal behavior evolves over time, such as seasonal changes in pedestrian traffic or new construction that alters the scene's structure. Continuous adaptation mechanisms, such as online fine-tuning or self-supervised retraining, are necessary to maintain robustness. However, such adaptation raises issues of data drift and concept drift, requiring monitoring and rollback procedures. The system architecture should therefore include a feedback loop that periodically evaluates model performance on a held-out validation set and triggers retraining when a performance degradation threshold is crossed. This operational aspect highlights the need for robust infrastructure that supports model lifecycle management, including version control, data provenance, and audit trails. From a governance perspective, robustness must be defined not only in terms of technical performance but also with respect to fairness and accountability. A system that is robust under certain conditions but systematically fails for particular demographic groups violates principles of equitable AI. The hierarchical motion decomposition approach, by focusing on motion rather than appearance, may reduce demographic biases because motion patterns are less correlated with race or gender than static features like skin color or clothing [12]. Nonetheless, biases can still arise from the training data if certain groups are underrepresented or if their typical motion patterns are mischaracterized as anomalous. This issue demands careful curation of training datasets and the inclusion of diverse scenarios during validation.

5. Deployment, Governance, and Policy Implications

Deploying video anomaly detection at scale involves more than algorithmic performance; it requires a socio-technical system that integrates hardware, networking, data storage, user interfaces, and human oversight. The hierarchical architecture we describe is computationally intensive relative to simpler models, which places demands on the underlying infrastructure. For city-wide surveillance networks with thousands of cameras, the cumulative cost of GPU servers, cooling, power, and networking can be substantial. Edge computing offers a partial solution by pushing smaller models to camera modules or local gateways, but the full hierarchical decomposition may be too heavy for resource-constrained edge devices. A hybrid cloud-edge deployment strategy can be effective: lightweight fine-grained motion streams are

processed at the edge, while mid-level and coarse streams are transmitted to a central server for more complex analysis. This partitioning must be designed with privacy considerations in mind, as transmitting raw video feeds raises concerns about surveillance and data misuse. To address privacy, we advocate for the adoption of anonymization techniques, such as blurring faces or embedding motion features directly rather than sending pixel images [13]. Policy frameworks for video surveillance are often fragmented across jurisdictions, but there is growing consensus on the need for transparency, consent, and oversight. The hierarchical motion decomposition approach, by offering per-stream interpretable scores, supports the accountability requirement: an operator can review why an alert was raised and verify that the decision was not based on biased or irrelevant features. Additionally, the system can be audited by third parties using a standardized protocol that checks for fairness across demographic subgroups [14]. The concept of "algorithmic impact assessments" has been proposed in the European Union's AI Act and similar regulations; our architectural extensions are designed to facilitate such assessments by providing well-defined, decomposable outputs. Another policy dimension concerns the potential for mission creep: systems intended for anomaly detection can be repurposed for generalized surveillance or behavioral profiling. To mitigate this, governance mechanisms should enforce purpose limitation, data retention policies, and periodic re-evaluation of system necessity. Technical measures such as differential privacy can be integrated into the training process to ensure that the model does not memorize specific individuals [15]. The sustainability of large-scale video analytics also merits attention. The energy consumption of deep neural networks has become a significant environmental concern [16]. Our hierarchical architecture, while more efficient than some ensemble approaches, still requires considerable computational resources. We estimate that a full-scale deployment with 10,000 cameras could consume on the order of hundreds of kilowatt-hours per day, equivalent to the energy usage of several households. To reduce the carbon footprint, we propose using asynchronous processing: the fine-grained stream runs continuously, while the coarse stream is activated only when a certain threshold of motion activity is detected. Such adaptive processing can cut energy usage by up to 40% without significantly degrading detection accuracy. Further sustainability gains can be achieved by training models with knowledge distillation from larger teacher models to smaller student models, thereby reducing inference costs [17]. These considerations must be embedded into procurement policies and operational guidelines.

6. Sustainability and Fairness Considerations

Sustainability in the context of AI systems extends beyond energy efficiency to encompass the entire lifecycle, including data collection, model training, deployment, and decommissioning. The hierarchical motion decomposition approach, by decoupling motion streams, allows for selective retraining: only the stream that detects a drift in motion patterns needs to be updated, rather than retraining the entire model. This reduces the computational resources required for continuous learning. However, the data collection itself—across multiple sites and temporal periods—can be resource-intensive and may involve thousands of hours of video. Ethical data sourcing practices, such as using publicly available datasets or synthetic data generation, can reduce the environmental and social costs. Fairness is a multidimensional concern that includes demographic parity, equalized opportunity, and counterfactual fairness. In video anomaly detection, false positive rates that differ across demographic groups can lead to disproportionate number of unwarranted alerts for certain populations, causing harassment or reputational harm. Our architecture's reliance on motion rather than appearance provides a structural advantage, but it is not a guarantee. To explicitly

enforce fairness, we incorporate a fairness regularization term during training that penalizes disparities in false positive rates across groups defined by scene context (e.g., different areas of a city) or pedestrian attributes (e.g., age, if labels are available). Because direct demographic labels are often unavailable, we use proxy variables such as location and time of day [18]. This approach has limitations—proxy variables can introduce new biases—so continuous monitoring with human-in-the-loop auditing remains essential. The governance framework for fairness should also include a mechanism for affected communities to contest automated decisions. For instance, if an anomaly alert results in a security intervention, individuals should have the right to request a review of the model's output. The hierarchical scoring system facilitates such reviews by providing a detailed decomposition of why the event was flagged. We argue that technical architectures must be designed with contestability in mind, which is a principle increasingly recognized in AI ethics guidelines [19]. The sustainability of fairness measures themselves must be considered: post-processing adjustments may degrade accuracy for all groups, and the cost of maintaining fairness across a dynamic environment can be high. Therefore, we recommend periodic fairness audits with thresholds that trigger corrective actions, integrated into broader model governance pipelines.

7. Conclusion

This paper has presented a comprehensive analysis of robust video anomaly detection through the lens of hierarchical motion decomposition, building on the HY-Himmel architecture. We have shown that extending this architecture with multi-stream motion encoding, hierarchical scoring, and contrastive learning yields significant improvements in robustness to domain shifts and reduction in false alarms. The structural trade-offs, including computational cost, memory footprint, and latency, were examined in the context of real-world deployment scenarios, highlighting the need for hybrid cloud-edge strategies and adaptive processing. Beyond technical performance, we engaged with governance, policy, and ethical dimensions, arguing that hierarchical designs support interpretability, fairness, and accountability. Sustainability considerations, from energy consumption to lifecycle management, were integrated into the architectural discussion, emphasizing the importance of holistic evaluation. The extensions proposed here are not merely incremental algorithmic improvements; they represent a shift toward designing anomaly detection systems that are aligned with human cognitive models and societal values. Future work should explore dynamic hierarchies that learn optimal temporal scales for different environments, as well as federated learning frameworks that enable collaborative training across institutions without sharing sensitive video data. As video surveillance continues to expand globally, the need for robust, fair, and sustainable anomaly detection will only intensify. The hierarchical motion decomposition principle offers a promising path forward, provided that technical innovation is paired with thoughtful governance and continuous stakeholder engagement.

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