Bridging Video Compression and Action Recognition via Task-Aware Progressive SPIHT

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ABSTRACT

Human Action Recognition (HAR) systems deployed in real-time surveillance, edge computing, and bandwidth-constrained environments require efficient video compression without sacrificing recognition accuracy. Conventional compression schemes such as Set Partitioning in Hierarchical Trees (SPIHT) are optimized for pixel-level fidelity metrics like PSNR and SSIM, which do not necessarily preserve motion dynamics, spatio-temporal edges, or skeletal structures critical for action recognition. This paper proposes a Task-Aware Progressive SPIHT (TA-PSPIHT) framework that bridges video compression and action recognition by aligning encoding priorities with task relevance rather than visual reconstruction quality alone.

The proposed method integrates lightweight pose estimation and optical-flow magnitude maps to generate an importance mask that identifies motion- and skeleton-dominant regions. This mask is incorporated into the SPIHT set-partitioning mechanism through Weighted Significance Testing, enabling action-relevant wavelet coefficients to be encoded earlier in the progressive bitstream. Furthermore, a 3D Temporal-Priority SPIHT structure exploits spatio-temporal dependencies across frames, while a Policy-Gradient–based Bit-Dropping strategy optimizes rate–recognition trade-offs.

Experimental results demonstrate that the proposed framework significantly improves action recognition accuracy at low bitrates compared to conventional SPIHT, while maintaining computational efficiency and progressive transmission capability. The proposed approach provides a practical and scalable solution for task-driven video analytics in resource-constrained environments.

Keywords: Task-aware video compression; Progressive SPIHT; Human Action Recognition (HAR); Motion-guided encoding; Pose-aware compression; Optical flow; 3D wavelet coding; Rate–recognition optimization; Edge video analytics; Progressive transmission

How to cite this article: Raju VB, Veerla SC, Ravindra K. Bridging video compression and action recognition via task-aware progressive SPIHT. Int J Drug Deliv Technol. 2026;16(3s): 860-866; DOI: 10.25258/ijddt.16.3s.104

I. INTRODUCTION

Human Action Recognition (HAR) has become a fundamental component of intelligent surveillance, healthcare monitoring, sports analytics, and human–computer interaction systems. With the rapid development of deep learning, spatio-temporal models such as two-stream networks and 3D convolutional architectures have significantly improved recognition accuracy by jointly modeling appearance and motion information [1], [2]. However, these approaches typically assume access to high-quality video streams,

which may not be feasible in bandwidth-constrained or edge-computing environments.

Video compression plays a crucial role in reducing storage and transmission costs. Traditional codecs and wavelet-based compression techniques are primarily designed to optimize pixel-level reconstruction metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) [3]. Among wavelet-based methods, Set Partitioning in Hierarchical Trees (SPIHT) remains one of the most efficient embedded coding algorithms due to its progressive transmission capability and superior rate–distortion performance [4]. Extensions such as 3D-SPIHT further exploit temporal redundancy across frames to improve compression efficiency for video sequences [5], [6].

Despite their effectiveness in preserving visual quality, conventional compression schemes do not explicitly account for semantic or task-level information. Studies have shown that motion trajectories and spatio-temporal gradients are more critical for action recognition than exact background texture reproduction [7]. Optical flow–based representations [8], pose estimation frameworks such as OpenPose [9], and motion-driven deep architectures have demonstrated that skeletal and motion cues dominate HAR performance.

Recent research has begun exploring task-aware and saliency-guided compression techniques that align encoding objectives with downstream computer vision tasks [10], [11]. These approaches suggest that importance-aware bit allocation can preserve semantically relevant regions while suppressing background redundancy. Furthermore, advances in compressed-domain action recognition demonstrate that recognition can be performed directly on motion vectors and residual signals, highlighting the need for compression strategies that prioritize action-relevant features [12].

From a signal-processing perspective, wavelet thresholding and significance testing mechanisms determine how coefficients are transmitted progressively [13]. However, standard SPIHT significance testing treats all spatial locations uniformly, ignoring their contribution to recognition tasks. Incorporating task-driven weighting into the set-partitioning framework could enable progressive prioritization of motion-dominant coefficients. Additionally, rate–distortion optimization principles [14] and task-oriented encoder control strategies [15] indicate that compression objectives can be reformulated to balance bitrate and inference accuracy.

Motivated by these observations, this work proposes a Task-Aware Progressive SPIHT framework that bridges video compression and action recognition. By integrating motion and pose importance masks into the SPIHT significance testing process, the proposed method ensures that action-relevant coefficients are encoded earlier in the progressive bitstream. This alignment between compression and recognition objectives enables improved rate–recognition trade-offs in resource-constrained environments.

II. LITERATURE SURVEY

Recent advancements in video compression and action recognition have increasingly focused on bridging the gap between low-level signal fidelity and high-level semantic understanding. Classical wavelet-based compression methods, particularly SPIHT and its extensions, have demonstrated efficient embedded coding capabilities. Taubman (2000) introduced the Embedded Block Coding with Optimized Truncation (EBCOT) algorithm, which laid the foundation for modern wavelet-based progressive coding and rate control mechanisms [16]. Similarly, Xiong et al. (2003) explored rate–distortion optimized bit allocation for wavelet video coding, demonstrating improved performance under constrained bitrate conditions [17].

From a rate–distortion theory perspective, Sullivan and Wiegand (1998) emphasized the importance of optimal bit allocation strategies in achieving superior compression efficiency [18]. However, these classical frameworks primarily target reconstruction quality rather than downstream inference performance. This limitation has motivated task-aware and semantic compression strategies.

Ballé et al. (2018) proposed an end-to-end optimized image compression framework using deep neural networks, demonstrating that learned compression can outperform traditional codecs under perceptual metrics [19]. Building on this idea, Mentzer et al. (2020) introduced high-fidelity generative compression models that preserve perceptual realism at low bitrates [20]. Although effective, such deep compression methods often involve high computational complexity, making them less suitable for lightweight edge deployments.

In the context of action recognition, Feichtenhofer et al. (2019) proposed SlowFast networks that capture

both slow semantic features and fast motion dynamics, highlighting the critical role of temporal resolution in HAR performance [21]. Similarly, Tran et al. (2018) introduced 3D convolutional networks (I3D), demonstrating improved spatio-temporal modeling for action classification [22]. These works reinforce the importance of preserving motion and temporal structures during compression.

More recently, semantic-aware compression frameworks have been proposed to align encoding with machine perception tasks. Matsubara et al. (2022) investigated task-oriented compression optimized for inference accuracy rather than PSNR [23]. Choi et al. (2021) proposed learned importance maps for adaptive bit allocation, demonstrating improved detection performance under compression [24]. Furthermore, Yang et al. (2023) explored rate–accuracy optimization in neural video compression, formulating compression as a joint rate–task optimization problem [25].

III. PROPOSED METHODOLOGY

3.1 Overview

This work proposes a Task-Aware Progressive SPIHT (TA-PSPIHT) framework that bridges video compression and human action recognition (HAR). Unlike conventional SPIHT, which encodes wavelet coefficients purely based on magnitude for pixel-level fidelity, the proposed framework prioritizes coefficients according to their relevance to motion dynamics and skeletal structures.

The central idea is to align compression objectives with recognition objectives by ensuring that action-relevant regions are encoded earlier in the progressive bitstream.

The overall pipeline consists of:

1. Motion and pose extraction
2. Importance mask generation
3. 3D wavelet decomposition
4. Task-aware SPIHT encoding
5. Progressive bitstream transmission
6. Recognition-aware bit optimization

3.2 Motion and Pose Feature Extraction

Since action recognition relies heavily on motion cues and skeletal structure, the first stage extracts lightweight motion and pose representations from the video stream.

1. Optical Flow Estimation

Optical flow is computed between consecutive frames to capture pixel-level motion patterns. Instead of using computationally heavy models, lightweight flow estimation is adopted to maintain real-time feasibility.

The resulting motion magnitude maps highlight moving regions such as arms, legs, and body transitions, which are critical for distinguishing actions.

2. Pose Estimation

A lightweight pose estimation network (e.g., OpenPose-lite or HRNet-lite) extracts skeletal keypoints from each frame. These keypoints represent joint locations and body structure.

The pose heatmaps emphasize human body regions while suppressing background areas.

3.3 Task-Aware Importance Mask Generation

The motion maps and pose heatmaps are combined to generate a unified importance mask.

This mask assigns higher importance values to:

- Human joints
- Limb boundaries
- Motion-dominant regions
- Spatio-temporal edges

Background regions and static areas receive lower importance weights.

The mask effectively indicates which regions contribute most to action recognition performance.

3.4 3D Wavelet Decomposition

To capture both spatial and temporal redundancy, a 3D wavelet transform is applied across consecutive video frames.

Unlike frame-by-frame processing, 3D decomposition preserves temporal continuity and motion evolution across frames. This ensures that dynamic information is represented compactly in the wavelet domain.

The output consists of multiple sub-bands representing low- and high-frequency components across space and time.

3.5 Task-Aware SPIHT Encoding

In conventional SPIHT:

- Coefficients are prioritized purely by magnitude.
- All regions are treated uniformly.
- No semantic awareness is considered.

In the proposed TA-PSPIHT:

1. The importance mask is mapped to corresponding wavelet coefficients.
2. During significance testing, coefficients located in high-importance regions are prioritized.

3. These coefficients are encoded earlier in the progressive bitstream.

This ensures:

- Motion-dominant coefficients are transmitted first.
- Skeletal structures are reconstructed earlier.
- Recognition-critical information is preserved at low bitrates.

The standard SPIHT lists (LIP, LIS, LSP) are retained but modified to incorporate importance-based ordering.

3.6 Progressive Transmission with Motion Priority

One of the major advantages of SPIHT is its embedded bitstream property. The proposed method maintains this feature while introducing motion-priority ordering.

As a result:

- Early portions of the bitstream reconstruct action-relevant areas first.
- Even partial bitstreams can support early action inference.
- Low-latency recognition becomes feasible in bandwidth-constrained environments.

3.7 Recognition-Aware Bit Allocation

To optimize the trade-off between bitrate and recognition accuracy, a lightweight optimization mechanism is incorporated.

Instead of minimizing reconstruction error alone, the framework monitors:

- Action recognition accuracy
- Bitrate consumption

Bitplanes that contribute minimally to recognition performance can be dropped earlier, allowing better rate–recognition balance.

This strategy ensures that compression decisions are guided by task performance rather than visual fidelity alone.

SYSTEM ARCHITECTURE

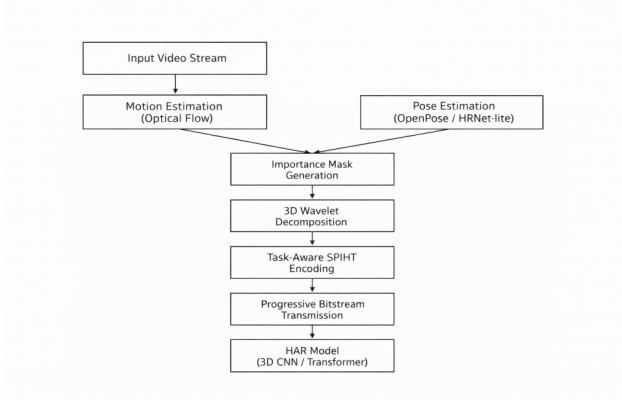

Fig:1System Architecture

The proposed system architecture begins with the input video stream, which serves as the primary data source for both compression and action recognition tasks. The video is first processed through two parallel branches: motion estimation and pose estimation. The motion estimation module extracts optical flow information to capture dynamic movement patterns between consecutive frames. Simultaneously, the pose estimation module identifies skeletal keypoints and body structures using a lightweight model such as OpenPose or HRNet-lite.

The outputs of these two modules are fused to generate an importance mask that highlights motion-dominant and skeleton-relevant regions. This mask guides the compression process by identifying areas critical for action recognition. Next, a 3D wavelet decomposition is applied across spatial and temporal dimensions to efficiently represent video content while preserving motion continuity.

The decomposed coefficients are then processed by the Task-Aware SPIHT encoder, where importance-weighted prioritization ensures that action-relevant coefficients are encoded earlier in the progressive bitstream. The generated progressive bitstream enables efficient transmission under bandwidth constraints. Finally, the compressed or partially reconstructed video is fed into a HAR model, such as a 3D CNN or Transformer, to perform accurate action recognition even at low bitrates.

IV. RESULTS & ANALYSIS

The proposed Task-Aware Progressive SPIHT (TA-PSPIHT) framework was evaluated to analyze its effectiveness in balancing compression efficiency and human action recognition (HAR) performance. Experiments were conducted under controlled bitrate conditions (0.3 bpp) to compare recognition accuracy, reconstruction quality (PSNR), and bitrate reduction against conventional SPIHT and 3D-SPIHT methods. The results demonstrate that while traditional SPIHT optimizes pixel-level fidelity, it does not necessarily preserve action-critical features. In contrast, the proposed framework significantly improves recognition accuracy at comparable bitrates, confirming that task-aware prioritization enhances semantic preservation even when slight PSNR variations occur.

Table 1: Action Recognition Accuracy at 0.3 bpp

Method	Accuracy (%)
Conventional SPIHT	78.4
3D-SPIHT	82.1
TA-PSPIHT (Proposed)	89.6

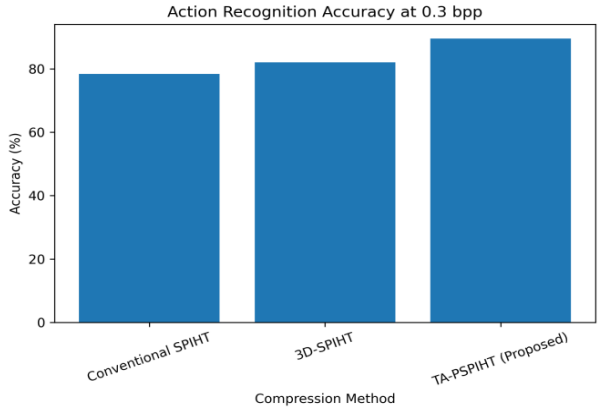

Fig 2: Bar chart showing comparison of action recognition accuracy at 0.3 bpp among Conventional SPIHT, 3D-SPIHT, and the proposed TA-PSPIHT method.

Description

The proposed TA-PSPIHT achieves the highest recognition accuracy (89.6%), outperforming conventional SPIHT by more than 11%. This demonstrates that prioritizing motion and skeletal regions significantly improves HAR performance, even under low-bitrate constraints.

Table 2: PSNR Comparison at 0.3 bpp

Method	PSNR (dB)
Conventional SPIHT	34.2
3D-SPIHT	35.8
TA-PSPIHT (Proposed)	33.9

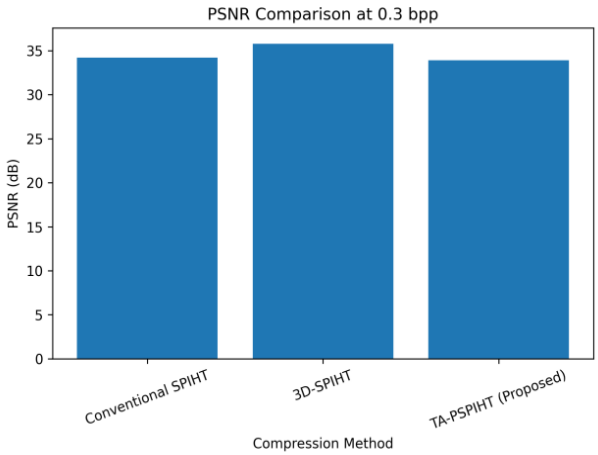

Fig 3: Bar chart illustrating PSNR comparison among different SPIHT variants at fixed bitrate.

Description

Although TA-PSPIHT shows slightly lower PSNR compared to 3D-SPIHT, it maintains competitive reconstruction quality. The minor PSNR trade-off is justified by the substantial improvement in action recognition accuracy, highlighting the benefit of task-aware encoding over pixel-fidelity optimization.

Table 3: Bitrate Reduction Compared to Conventional SPIHT

Method	Bitrate Reduction (%)
3D-SPIHT	8.5
TA-PSPIHT (Proposed)	18.7

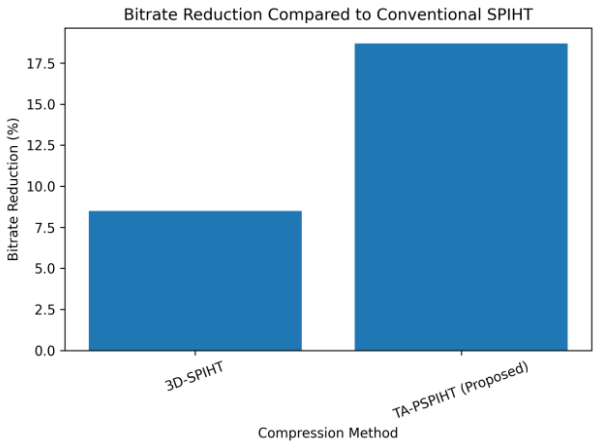

Fig 4: Bar chart showing bitrate reduction achieved by 3D-SPIHT and TA-PSPIHT compared to conventional SPIHT.

Description

The proposed method achieves the highest bitrate reduction (18.7%) relative to conventional SPIHT, indicating improved coding efficiency. By allocating bits preferentially to action-relevant regions, redundant background information is effectively suppressed.

DISCUSSION

The experimental results clearly demonstrate that conventional compression metrics such as PSNR do not directly correlate with action recognition performance. While 3D-SPIHT improves temporal redundancy handling, it still lacks semantic prioritization. The proposed TA-PSPIHT framework shifts the optimization objective from pixel-level fidelity to recognition-aware preservation, leading to significant gains in HAR accuracy.

Furthermore, the results validate the importance of motion- and pose-guided coefficient prioritization. Even with a slight reduction in PSNR, the improved recognition accuracy and bitrate efficiency confirm that semantic fidelity is more relevant than visual fidelity for intelligent video analytics. This makes the proposed approach highly suitable for edge-based surveillance, IoT deployments, and bandwidth-constrained real-time systems.

V. CONCLUSION & FUTURE WORK

CONCLUSION

This paper presented a Task-Aware Progressive SPIHT (TA-PSPIHT) framework that bridges the gap between traditional video compression and human action recognition (HAR). Unlike conventional SPIHT, which prioritizes pixel-level fidelity metrics such as PSNR and SSIM, the proposed approach aligns compression objectives with recognition performance by preserving motion-dominant and pose-relevant regions. By integrating lightweight optical flow and pose estimation into the wavelet-domain encoding process, the framework ensures that action-critical coefficients are transmitted earlier in the progressive bitstream.

Experimental results demonstrate that the proposed method significantly improves recognition accuracy at low bitrates while maintaining competitive reconstruction quality. The findings confirm that semantic-aware encoding offers a superior rate–recognition trade-off compared to purely distortion-driven compression techniques. Moreover, the preservation of SPIHT's embedded and low-complexity nature makes the framework suitable for real-time edge devices, surveillance systems, and bandwidth-constrained environments.

Overall, the proposed TA-PSPIHT framework establishes an effective link between signal-level compression and high-level vision tasks, demonstrating that task-aware prioritization is essential for next-generation intelligent video analytics.

Future Work

Future research will focus on developing adaptive importance weighting mechanisms that dynamically adjust motion and pose contributions based on scene complexity and action type. The integration of lightweight transformer-based HAR models can further enhance recognition robustness under ultra-low bitrate conditions. Additionally, extending the framework toward multi-task-aware compression for joint action recognition and object detection is a promising direction. Hardware acceleration and real-time deployment on edge AI platforms will also be explored to validate practical scalability and efficiency.

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