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A Survey on Feature Diversity Enhancement Techniques for Remote Sensing Video Super-Resolution

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Abstract: Remote sensing video super-resolution (VSR) is a vital technology enabling fine-grained Earth observation from satellites. With growing demands in applications such as envi ronmental monitoring, urban development, and disaster man- agement, improving the resolution of remote sensing videos has become paramount. Traditional video super-resolution methods, designed primarily for natural scenes, often fail to address the unique challenges posed by satellite imagery. This survey comprehensively reviews recent developments in feature diversity enhancement for VSR, focusing on the challenges of spatial, chan- nel, and temporal heterogeneity. We place particular emphasis on MADNet, a novel architecture that integrates Spatial Diversity Enhancement (SDE) and Channel Diversity Enhancement (CDE) into a Multi-Axis Diversity Module (MADM). Furthermore, we compare MADNet with state-of-the-art VSR models, analyze its architectural innovations, and identify future research directions. This paper aims to serve as a foundational resource for re- searchers and practitioners interested in high-fidelity satellite video reconstruction.

I. INTRODUCTION

In recent years, video satellites have gained significant attention for Earth observation due to their dynamic and continuous capture capabilities. Unlike static remote sensing images, video satellites can monitor specific areas over time, which is crucial for applications like object tracking, classification, and segmentation. However, the video data from these satellites often suffer from various quality-degrading factors such as satellite platform tremors, atmospheric scattering, compres- sion, and down sampling. These issues lead to significant loss of high-frequency spatial details, making it difficult to extract precise information. To address this, video super-resolution (VSR) emerges as a key technology aimed at reconstructing high-resolution (HR) videos from low-resolution (LR) inputs. VSR is inherently a more complex task than single- image super-resolution (SISR) due to the need for effective spatial-temporal feature aggregation across misaligned video frames. Traditional model-based methods, though once popu- lar, struggle with the complexity and variability in satellite video data. In contrast, deep learning-based VSR methods have shown substantial progress by leveraging architectures like sliding-window and recurrent networks. Sliding-window methods explore local temporal redundancy, while recurrent approaches particularly bidirectional propagation framework- shave demonstrated strong performance in modeling temporal motion. Despite their success, these models typically rely on static convolutions, which fail to capture the diverse spatial characteristics and high-frequency textures prevalent in satel- lite imagery.

The MADNet framework is introduced to address these lim- itations by enhancing feature diversity along multiple axesspa- tial, channel, and frequency domains.

MADNets core module, the Multi-Axis Diversity Enhancement Module (MADM), consists of three branches: a Spatial Diversity Enhancement (SDE) module using multiple learnable filters for capturing varied local spatial patterns; a Channel Diversity Enhancement (CDE) module that leverages discrete cosine transform (DCT) to enrich frequency-based feature representations; and an aux- iliary branch with static convolutions to retain spatial-invariant features. This parallel structure enables effective encoding of spatial-temporal information while preserving high-frequency details critical for remote sensing tasks.

Overall, MADNet not only improves the spatial-temporal aggregation capability but also introduces a lightweight yet powerful mechanism for capturing heterogeneous feature pat- terns in satellite videos. Experimental results validate MAD- Nets superiority over state-of-the-art models, achieving notable improvements in peak signal-to-noise ratio (PSNR) and per- ceptual quality across multiple satellite datasets such as JiLin- 1, Carbonite-2, SkySat-1, and UrtheCast.

II. BACKGROUND AND MOTIVATION

A. Remote Sensing Video Characteristics

1) High Altitude Effects: Viewpoint variation introduces spatial inconsistencies.
2) Low Temporal Resolution: Frame gaps and sparsity reduce continuity.
3) Spectral Complexity: Terrain and man-made structures exhibit diverse textures.

B. Challenges in VSR

1) Temporal misalignment due to satellite motion.
2) Loss of high-frequency information in compression.
3) Inadequate feature modeling in traditional CNNs.

C. Need for Feature Diversity Enhancement

Most VSR models assume spatial/channel homogeneity. However, remote sensing data is heterogeneous by nature, requiring dynamic modeling via adaptive modules.

III. LITERATURE SURVEY

A. HR Siam: High-resolution Siamese network, towards space-borne satellite video tracking J. Shao, B. Du, C. Wu, M. Gong, and T. Liu,(2021)

METHODOLOGY: Real-Time Performance: 30 frames per second (FPS), making it suitable for real-time applications Siamese Network Compares the target object from a previ- ous frame with the current frame to find its new location. Pixel-level Refinement Module (PRM) Fine-tunes the rough prediction to more accurately locate the object at the pixel level. LIMITATIONS :Dependence on Motion Information in situations where targets are stationary or exhibit minimal movement, the system may struggle to maintain accurate tracking.

B. High Similarity-Pass attention for single image super- resolution J.-N. Su, M. Gan, G.-Y. Chen, W. Guo, and C. L. P. Chen(2024)

METHODOLOGY: Interpretability and Visualization-The paper provides visual analysis of the attention maps, showing that HSPA effectively attends to relevant structures (like tex- tures and edges), offering better interpretability of the model's behavior. HSPA (High-Similarity-Pass Attention):Filters out irrelevant features and focuses only on similar ones to sharpen image details. HSPAN (High-Similarity-Pass Attention Net- work):A full network that combines local and global (non- local) features using HSPA to improve the clarity of upscaled images. LIMITATIONS: Performance Drop on Low-Detail Im- ages: For low-resolution images with minimal structural infor- mation, the similarity-pass mechanism may fail to find useful correspondences, leading to less effective reconstruction.

C. BasicVSR: The search for essential components in video super-resolution and beyond K. C. K. Chan, X. and C. C. Loy(2021)

METHODOLOGY: Optical flow (from pre-trained models like SPyNet) is used to guide the alignment of features between adjacent frames, helping the model maintain temporal consistency. Basic VSR-improves video resolution by combin- ing information from past and future frames. BasicVSR++- enhances this with better alignment and deeper feature learn- ing. LIMITATIONS: Lack of Real-Time Efficiency Metrics:

Although lightweight, the paper does not fully benchmark runtime performance or latency on edge devices, which could be important for real-world deployment.

D. Event adapted video super-resolution Z. Xiao, D. Kai, Y. Zhang, Z.-J. Zha, X. Sun, and Z. Xiong,

METHODOLOGY: Superior Performance Achieves state- of-the-art results on several benchmarks (GoPro, REDS, HQF, etc.).Especially excels in scenarios with fast motion or blur, where traditional VSR methods struggle Event-Adapted Align- ment (EAA) Unit-Aligns multiple video frames using event data. Event-Adapted Fusion (EAF) Unit-Fuses aligned frames with event data to reconstruct high-resolution frames. LIM- ITATIONS: Limited Generalization to Real-World Data Most experiments use synthetic or lab-controlled datasets. Perfor- mance in real-world outdoor or low-light scenarios with real event camera input is not well demonstrated.

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E. Basic VSR++: Improving video super-resolution with enhanced propagation and alignment K. C. K. Chan, S. Zhou, X. Xu, and C. C. Loy(2022)

METHODOLOGY: Flow-Guided Deformable Alignment Combines optical flow with deformable convolution to align features across frames effectively. This method leverages the strengths of both techniques, achieving better alignment in challenging scenarios while maintaining training stabil- ity Second-Order Deformable Alignment-Learns how objects move between frames (e.g., a hand moving),Adjusts the position of those objects before enhancing them LIMITA- TIONS: Training Complexity The integration of second-order propagation and flow-guided deformable alignment increases the model's complexity, potentially leading to longer training times and higher computational requirements

F. J. Li, W. He, W. Cao, L. Zhang, and H. Zhang, 2024.

METHODOLOGY: Uncertainty Aware Fusion Module (UAFM) UAFM leverages the uncertainty ranking to perform level-by-level feature fusion across decoder stages. High- uncertainty pixels are processed more strongly, enabling the network to refine those regions progressively while retaining overall segmentation context. The result is a final refined map with reduced uncertainty and improved boundary accuracy LIMITATIONS: No Explicit Edge Supervision Unlike some GAN based or attention refinement methods that explicitly supervise boundary or edge pixels (e.g. reverse attention or edge aware loss), UANet does not incorporate specialized edge losses. Therefore, boundary sharpness improves indirectly via uncertainty but could be less precise than dedicated boundary modeling schemes

G. Q. Zhang, Q. Yuan, M. Song, H. Yu, and L. Zhang, , 2022.

METHODOLOGY :Spectral Low Rankness Prior (SLRP) Models the HSI as a third order tensor and applies Tucker decomposition to learn an orthogonal spectral basis and a reduced spectral factor .This exploits the globally correlated spectral low rank structure of hyperspectral data, enabling robust modeling of spectral redundancy and noise separa- tion. LIMITATIONS: Self Supervised Spatial Prior Sensitivity Training the CNN on the noisy input itself risks over fitting to noise, particularly if the noise dominates spatial details or lacks structural redundancy. The spatial priors strength depends heavily on the quality of the initialization and the noise level.

H. S. Chen, L. Zhang, and L. Zhang, 2023.

METHODOLOGY :Cross Scope Spatial spectral Trans- former (CST) Utilizes separate cross attention mechanisms across spatial and spectral dimensions, enabling the capture of long-range dependencies and intrinsic correlations in both domains simultaneously capability not supported by tradi- tional 2D/3D CNNs LIMITATIONS :Hyperparameter Sensitivity Performance depends on tuning of scales, attention head configurations, deformable sampling parameters, and depth of Transformer layers. Optimal hyperparameter selection may vary across datasets and requires careful cross-validation.

I. Y. Jo, S. W. Oh, J. Kang, and S. J. Kim, 2018.

METHODOLOGY: Dynamic Up sampling Filters (DUF) The network predicts per-pixel, dynamic up sampling filters based on a local spatial temporal neighborhood from mul- tiple LR frames (typically 3 frames centered on the tar- get frame).Each pixel in the high-resolution (HR) output is generated by applying a predicted local filter (e.g. 5) to the corresponding location in the center LR frame, thereby bypassing explicit motion estimation or compensation alto- gather. This allows reconstruction of sharper HR frames by implicitly leveraging motion cues. LIMITATIONS: No Long- Term Temporal Consistency Mechanism With a fixed temporal window (e.g. 7 frames), the model doesn't explicitly enforce longer-range temporal coherence or consistency across frames beyond that window.

D. Ilg, N. Mayer, T. Saikia, M. Keuper 2017.

METHODOLOGY: Specialized Subnetwork for Small Dis- placements (FlowNetSD) To better capture fine-grained motion, FlowNet includes a dedicated small motion network (denoted FlowNetSD) with modified strides and decoder con- nections. It specializes in refining subtle motion cues that standard networks often struggle with. Outputs from large- and small-motion branches are fused for the final dense floweld LIMITATIONS: Large Model Size and Resource Intensity With over million parameters, FlowNet demands substantial GPU memory and compute resources, making it less suitable for deployment on mobile or embedded hardware.

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IV. METHODOLOGY

Spatial diversity enhancement (SDE) that learns spatially- variant patterns, and channel diversity enhancement (CDE) that explores diverse inter-frequency correlations. Finally, we elaborate on the design pipeline of MADM based on the SDE and CDE.

A. Spatial Diversity Enhancement Module

Spatial Diversity Enhancement (SDE) Module Goal: Capture fine-grained spatial variations in satellite images.
Technique: Uses dynamic convolution, where kernel weights vary spatially, allowing learning of different filters per location. Performance: Aggregates a set of learnable kernel bases, Learns combination weights for these bases using a 3 GConv (Grouped Convolution). Applies the weighted kernels spatially to enhance representation.

B. Channel Diversity Enhancement Module(CDE)

Goal: Capture inter-frequency relationships across channels. Technique: Applies 2D Discrete Cosine Transform (DCT) to convert features into the frequency domain.
Performance Splits feature maps along the channel axis Applies DCT to each chunk and aggregates the frequency features,uses fully connected layers and sigmoid activation to adaptively fuse frequency-aware features.

C. Multi-Axis Diversity Module (MADM)

Combines SDE and CDE outputs. Uses a 5 DWConv for initial feature extraction. Merges spatial, channel, and aux- iliary branches to learn spatially-invariant and diverse pat- terns. Enhances overall model robustness and accuracy in VSR.

D. MADNet Architecture

1) SDE: Uses multiple learnable kernels.
2) CDE: DCT-based channel attention for frequency diver- sity.
3) Auxiliary branch: Learns global patterns.

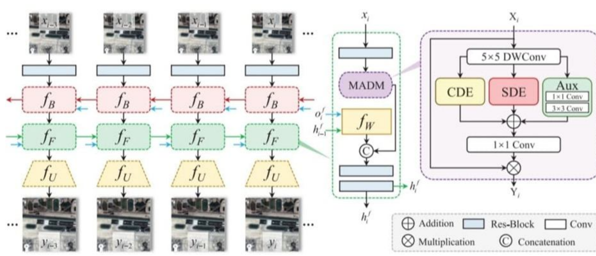

Fig. 1. Architecture of MADNet

Multi-Axis Diversity Module includes parallel SDE and CDE, followed by fusion.

E. Comparative Analysis

TABLE I
COMPARISON OF METHODS ON JILIN-1

Method	Type	PSNR	FLOPs	Params
EDVR	Sliding	35.51	High	Large
BasicVSR++	Recurrent	35.94	Medium	Medium
MADNet	Recurrent+MADM	36.35	Low	Compact

F. Effectiveness of Components

1) *Strengths:* Compared to the Base line model, CDE and SDE contribute to a PSNR improvement of 0.24dB and0.27dB, respectively. contribute to a PSNR improvement of 0.24dB and 0.27dB, respectively.

V. CONCLUSION

MADNet multi-axis feature diversity design makes it a strong candidate for remote sensing VSR tasks. With its lightweight structure and superior performance, it paves the way for real-time, onboard satellite video enhancement.

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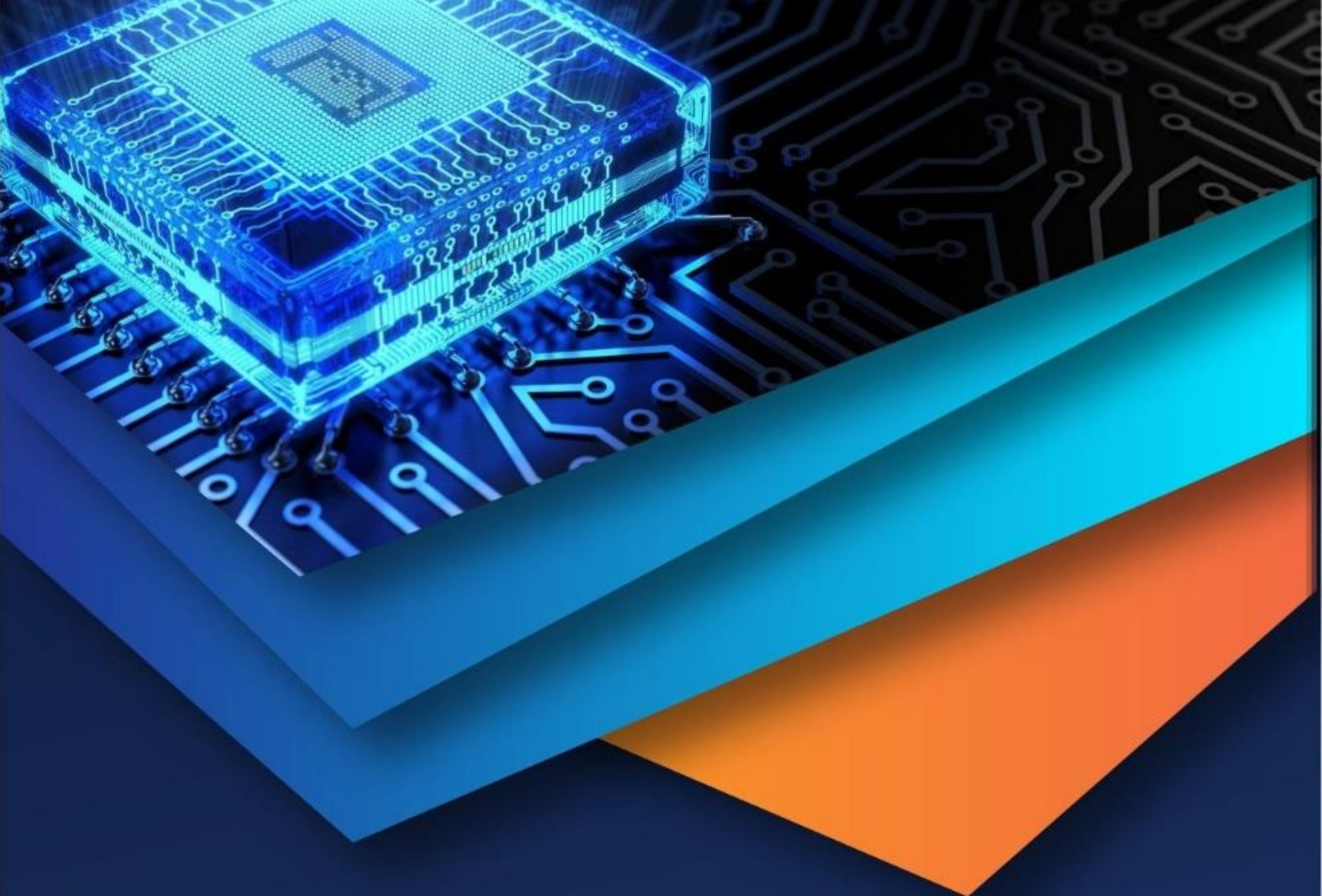

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