

# *VSRELL: Illuminating the Unseen*

*A New Approach to Video Enhancement in  
Low-Light*

*Presented by the Team from Tianjin University*

# The Problem We Address



## The Dual Challenge

Combining Video Super-Resolution (VSR) and Low-Light Enhancement (LLE) is a complex task due to intertwined degradations.



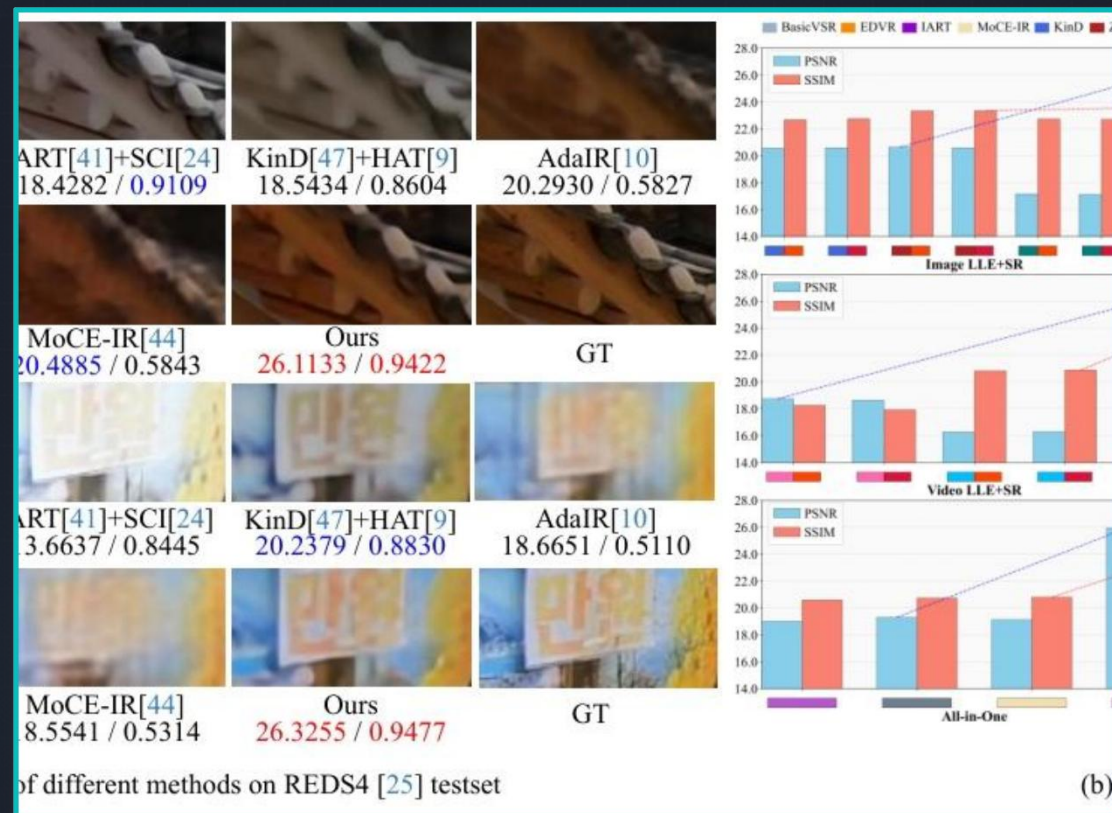
## The Degradation Cocktail

Low-light videos suffer from noise contamination, color distortion, and temporal inconsistency (flickering).



## Real-World Impact

Critical for applications like nighttime surveillance, autonomous driving, and mobile video quality.



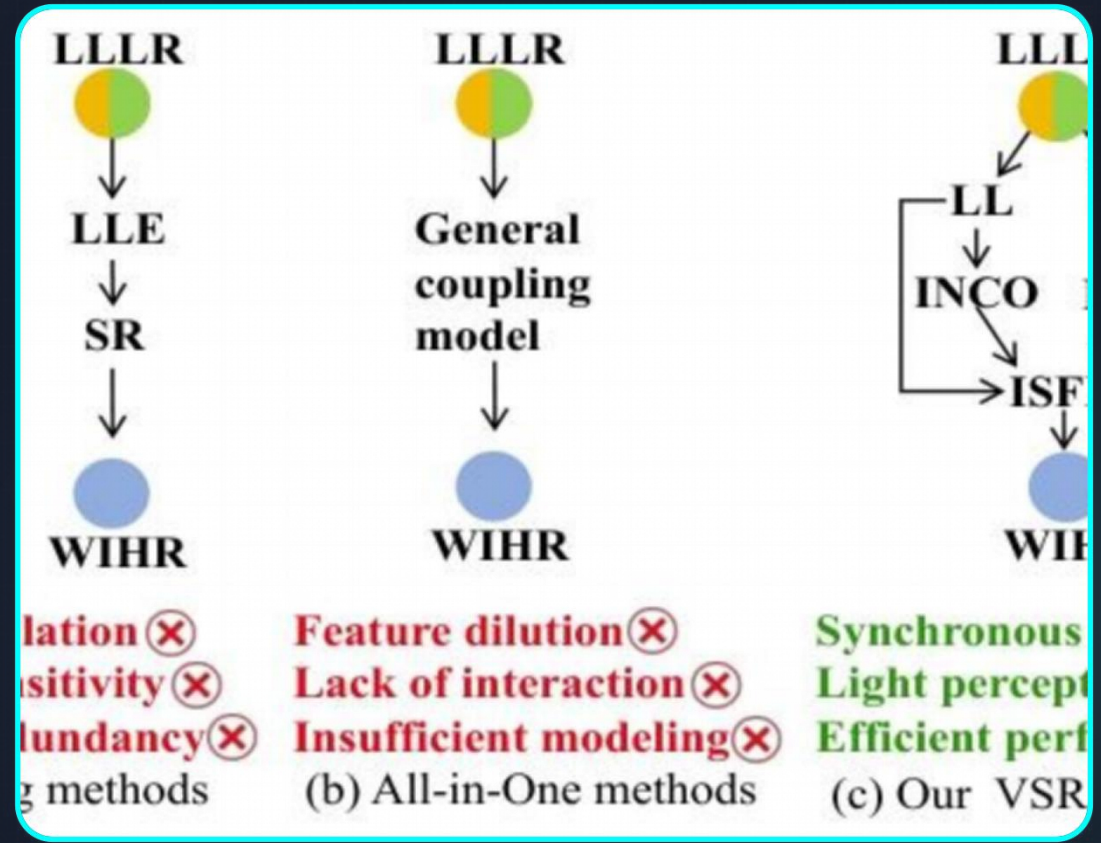
# Why Existing Methods Fall Short

## Cascaded Methods (LLE → VSR or VSR → LLE)

- **Error Accumulation:** Errors from the first step are amplified in the second.
- **Sequential Sensitivity:** The order of operations matters and can lead to suboptimal results.
- **Parameter Redundancy:** Inefficient use of computational resources.

## All-in-One Methods

- **Insufficient Modeling:** Often designed for single-type degradations, not the complex coupling of low-light and low-resolution.
- **Feature Dilution:** May struggle to disentangle different types of degradation.



# The Core Scientific Problems

01

## Noise-Color Coupling

Noise directly distorts color information in dark regions, making accurate color recovery a significant challenge.

02

## Inter-Frame (IF) Information Degradation

Noise obscures fine texture features between consecutive frames, significantly reducing the reliability of motion estimation algorithms.

03

## Inaccurate Optical Flow

Low-light environments drastically reduce gradient contrast, leading to frequent motion drift and spatial misalignment.

04

## Error Accumulation in Propagation

Initial feature degradation is amplified during long-range temporal propagation, causing severe and distracting temporal flickering artifacts.

# Introducing VSRELL: A Unified Approach

## A Unified Framework

VSRELL is the first CNN-based method to jointly solve Low-Light Enhancement (LLE) and Video Super-Resolution (VSR) in a single, cohesive end-to-end architecture.

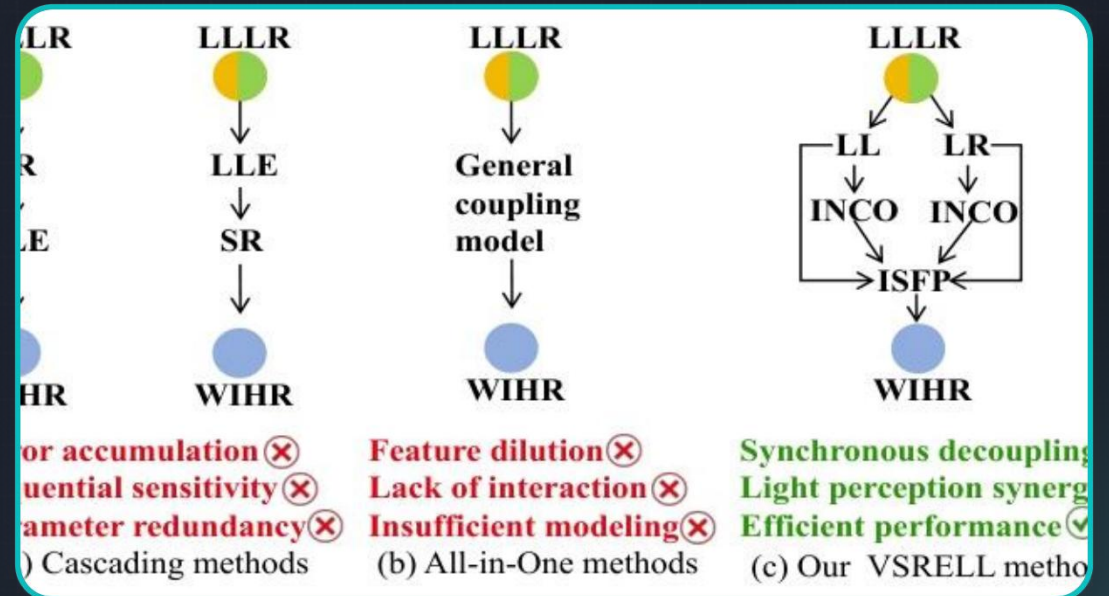
## Core Innovations

**INCO:** Illumination-Noise Co-Optimization — Jointly models and addresses the mutual influence of illumination variations and noise characteristics.

**ISFP:** Illumination-Sensitive Feature Propagation — Seamlessly integrates illumination information into feature propagation to preserve fine details.

## Our Primary Goal

To achieve **synchronous decoupling** of highly intertwined degradations (noise, blur, low-light) for both computation-efficient and high-quality visual restoration.



## Methodology & Performance

The diagram above compares VSRELL against state-of-the-art methods, highlighting our unique advantages in:

**“Synchronous Decoupling” | “High Efficiency”**

# Deep Dive: The INCO Module

## Illumination-Noise Co-Optimization



### Joint Modeling

Treats illumination enhancement and noise suppression as a single, coupled problem for optimal results.



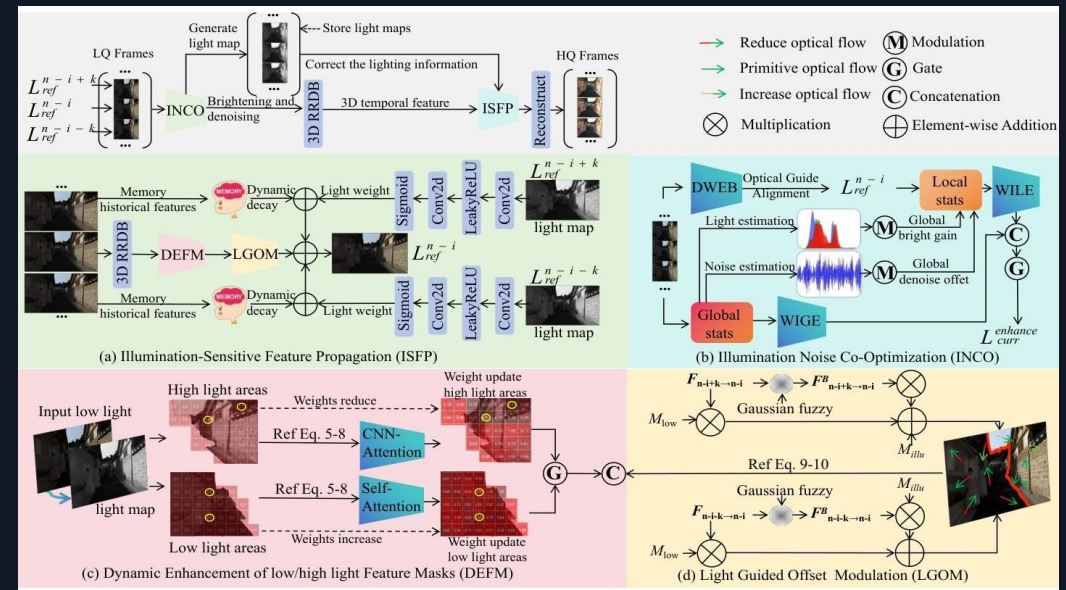
### Dynamic Window Partitioning

Analyzes sequences of frames to accurately model global illumination trends and noise statistics.



### Global-Local Feature Fusion

Combines overall scene context with fine-grained local details for a balanced enhancement effect.



### Adaptive Brightness Adjustment

Dynamically adjusts pixel gains to avoid common artifacts like over-exposure or under-exposure.

# Deep Dive: The ISFP Mechanism

## Illumination-Sensitive Feature Propagation



### Illumination-Aware Alignment

Adjusts motion estimation based on illumination, being more flexible in dark regions to avoid alignment errors.



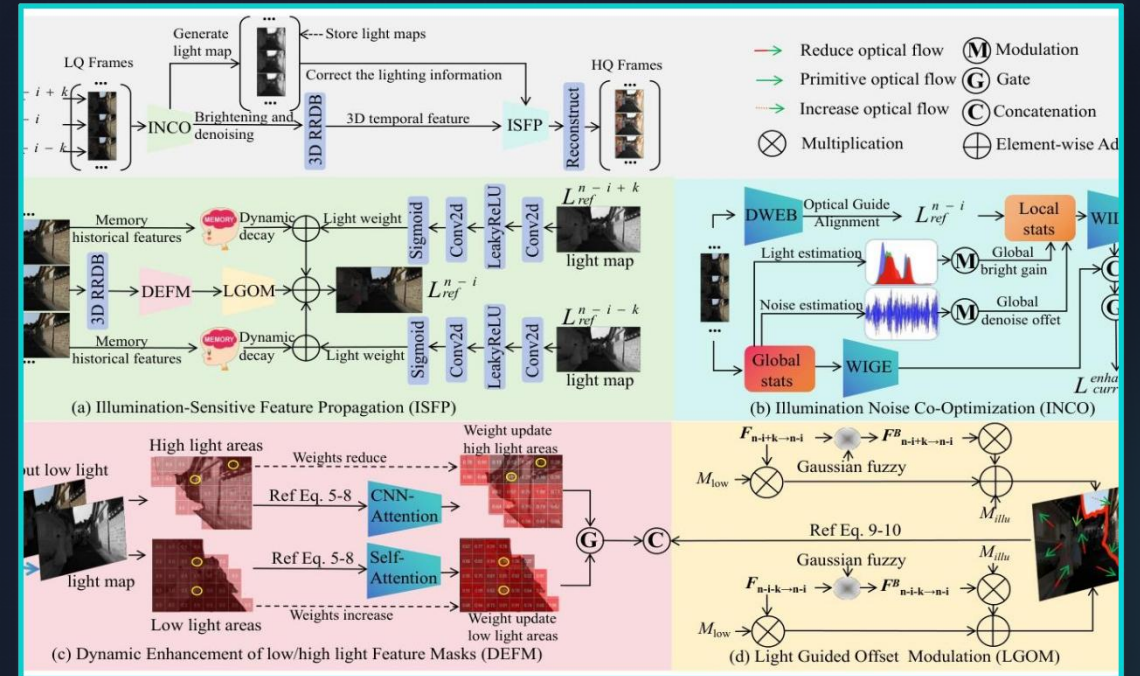
### Optical Flow-Adaptive Smoothing

Reduces noise in dark areas where signals are weak, while preserving fine details in bright, reliable regions.



### Dynamic Memory Decay

Intelligently weights features from past frames, downplaying unreliable frames to break the error accumulation chain.



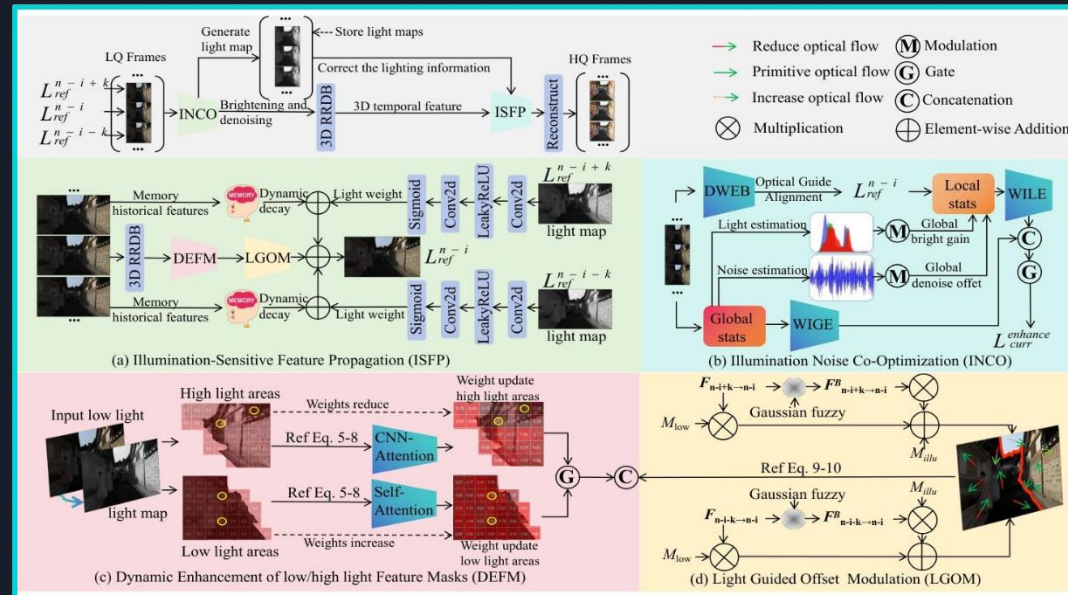
### VSRELL Architecture

Highlighting the ISFP (Illumination-Sensitive Feature Propagation) Module

# The Complete VSRELL Architecture

## End-to-End Pipeline

A single, unified network designed to handle the entire enhancement task in one streamlined pass, eliminating data fragmentation and inefficiency.



## Final Output

The result is a high-quality video stream with significantly enhanced brightness, upscaled resolution, and strong temporal consistency across all frames.

## Component Synergy: INCO + ISFP



The INCO (Input Correction) module prepares raw video features by cleaning up noise and artifacts. It then hands off the refined data to the ISFP (Inter-Frame Feature Propagation) module, which ensures these high-quality features are accurately and smoothly propagated across time, maintaining spatial and temporal coherence.

# How We Tested VSRELL



## DATASETS

- REDS (training & testing)
- Vid4 & UDM10 (generalization testing)



## COMPETITORS

- Comprehensive list of SOTA methods
- Cascaded combinations (e.g., SwinIR+KinD)
- All-in-One models (e.g., AdaIR, PromptIR)



## METRICS

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)

*Higher is better\**

# Quantitative Results: VSRELL is the New Leader



## SOTA Performance

VSRELL outperforms all compared methods on REDS4, Vid4, and UDM10 datasets, setting new benchmarks.



## Significant Gains

Achieves substantial improvements across the board in both PSNR and SSIM, the gold-standard image quality metrics.

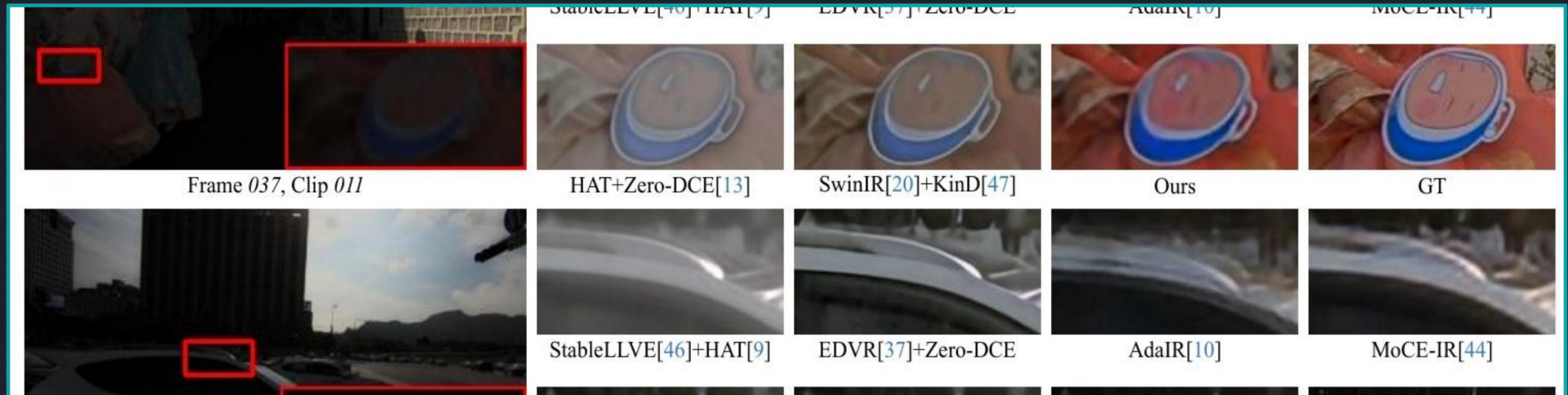


## Strong Generalization

Maintains high performance on completely unseen data, demonstrating excellent robustness to different distributions.

| Method               | REDS4 (PSNR / SSIM)                     | Vid4 (PSNR / SSIM)                      | UDM10 (PSNR / SSIM)                     |
|----------------------|---|---|---|
| Method A (SOTA)      | 32.51 / 0.8962                          | 31.89 / 0.8815                          | 30.12 / 0.8643                          |
| <b>VSRELL (Ours)</b> | <b>33.72 (+1.21) / 0.9105 (+0.0143)</b> | <b>33.15 (+1.26) / 0.8980 (+0.0165)</b> | <b>31.50 (+1.38) / 0.8801 (+0.0158)</b> |

# Qualitative Results: A Clear Difference



## Superior Visual Quality

VSRELL produces sharper details, more natural colors, and fewer artifacts compared to competing methods.

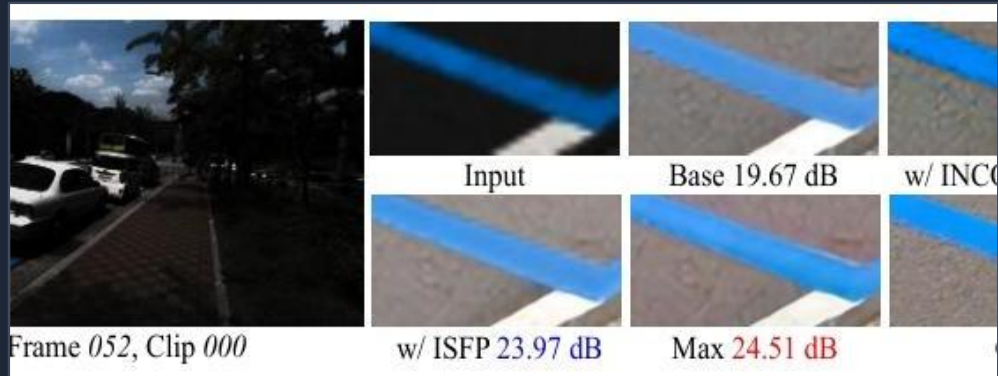
## Temporal Stability

Effectively suppresses flickering and maintains structural integrity in dynamic regions across frames.

## Realistic Enhancement

Strikes a perfect balance to avoid over-smoothing or creating artificial-looking, "plastic" results.

# Ablation Studies: Proving Our Components Work

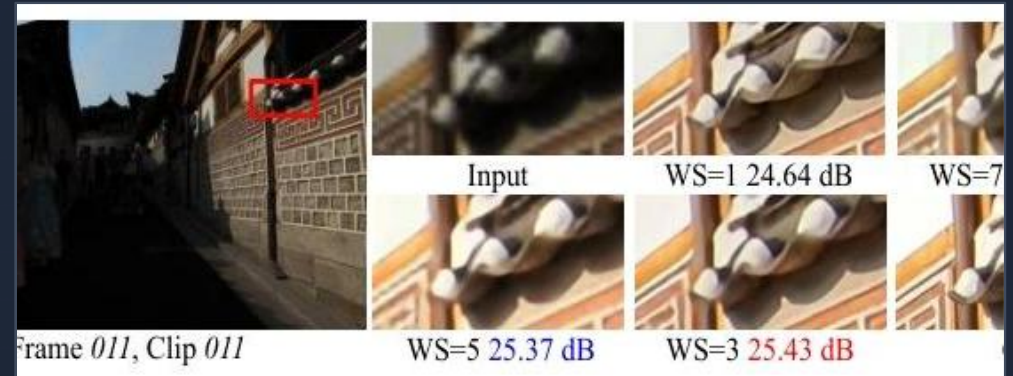


## INCO & ISFP are Essential

Ablation tests reveal that removing either INCO or ISFP module results in a significant performance degradation of over 0.8 dB in PSNR, demonstrating their critical role.

## Component Synergy

The integration of INCO and ISFP yields the best qualitative and quantitative results, proving the effectiveness of their combined design.



## Optimal Window Size

We systematically tested window sizes ranging from 1 to 7 frames. The data consistently showed that a window size of 3 frames (WS=3) achieves the best balance between computational efficiency and model accuracy.

This finding informed our final architecture, ensuring it is both lightweight and powerful.

# Conclusion



## A New Baseline

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*VSRELL provides a simple yet effective baseline for the challenging task of joint low-light video enhancement and super-resolution.*



## Proven Effectiveness

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*Both quantitative and qualitative results demonstrate VSRELL's superiority over existing methods.*



## Technical Contribution

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*The INCO and ISFP modules offer novel solutions to the problems of noise-color coupling and error accumulation in video restoration.*

# Future Work



## Handling More Complex Degradations

*Extend the current model to address more extreme and diverse multi-degradation scenarios. We aim to tackle combinations of heavy noise, motion blur, high compression artifacts, and low-light conditions that remain challenging for state-of-the-art restoration methods.*



## Efficiency & Deployment

*Optimize the model architecture for computational efficiency to enable seamless deployment on mobile and edge devices. The goal is to achieve real-time inference speeds without a significant drop in accuracy, unlocking practical use cases for everyday photography.*

THANK YOU!

# Questions & Answers

FEEL FREE TO ASK ANYTHING