# Deep blind light field image quality assessment by extracting angular and spatial information

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# Outline

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# Introduction & Motivation

## Introduction

Light Field Image (LFI)

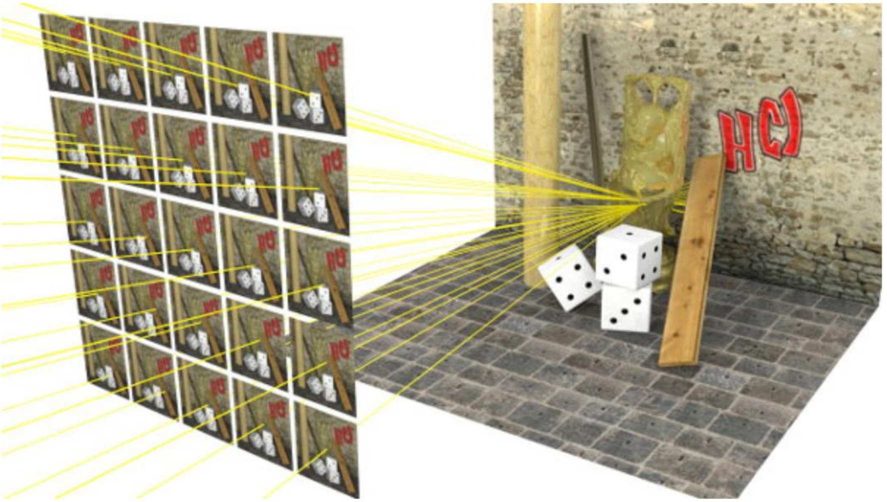
- A novel imaging format
- Provides powerful immersive experience

Generation of LFIs

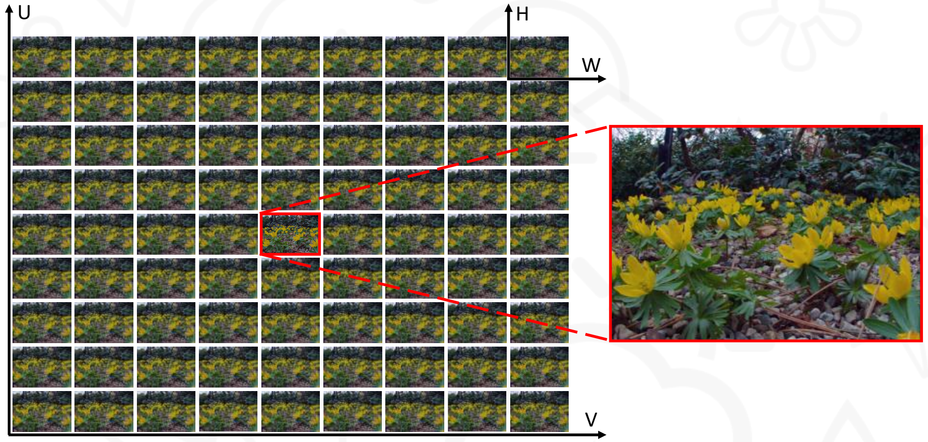
- Photographing the same scene from an array of viewpoints
- Narrow parallax

Typical representation of LFIs

- Sub-Aperture Image (SAI) array



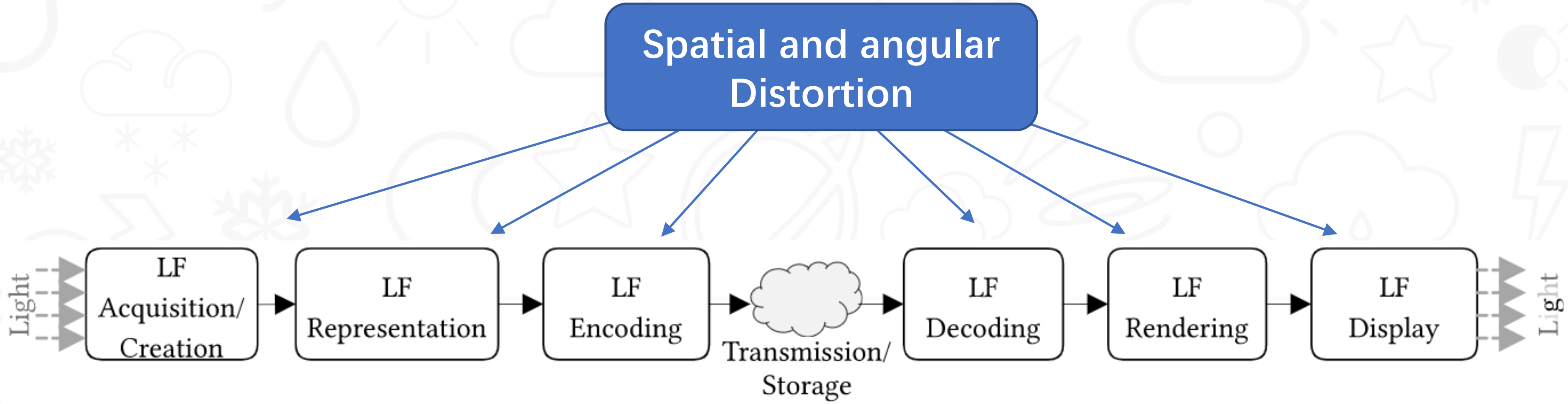
Generation of LFIs




Sub-Aperture Image (SAI) array of LFIs

# Introduction & Motivation

## Introduction




LFI processing chain

**Our focus: No-Reference Light Field Image Quality Assessment (NR LF-IQA) metric**

# Introduction & Motivation

## Motivation

Most existing NR LF-IQA metrics
- Hand-crafted features
- Fail to accurately predict the distorted LFI quality

Our work
- Discriminative features extracted by Convolutional Neural Network (CNN)
- Two new problems

➢ No enough LFI data for training a CNN model.

➢ No CNN model specifically designed for LF-IQA.

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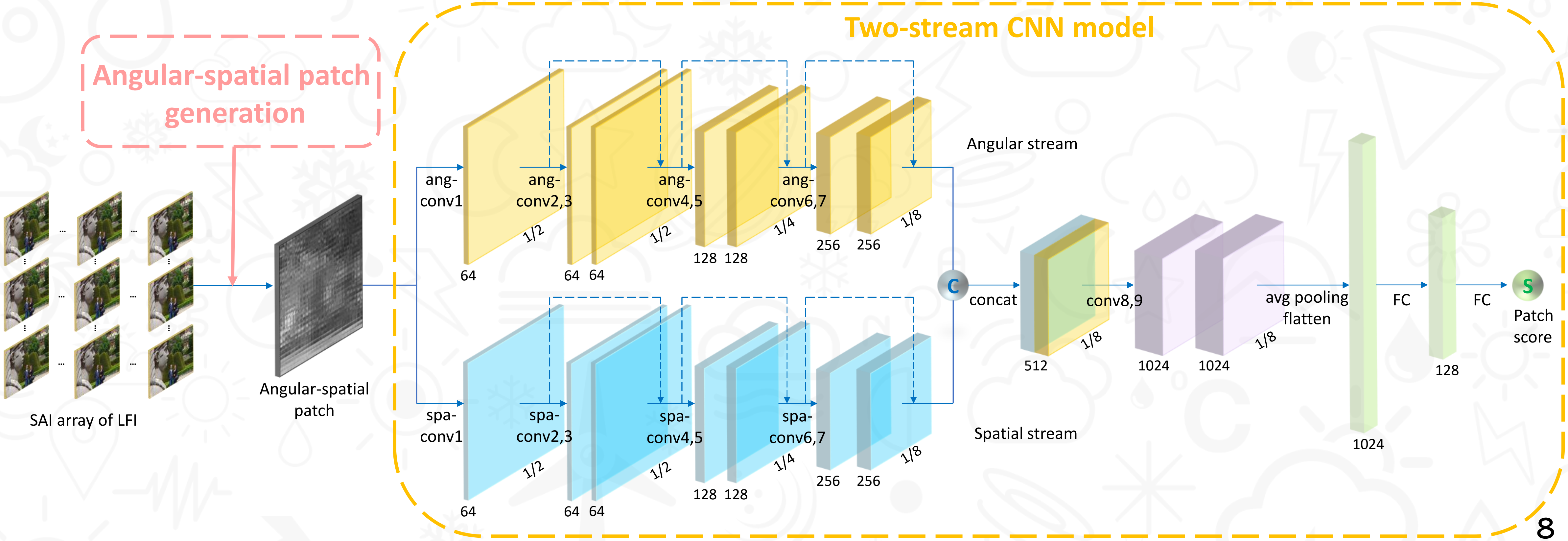
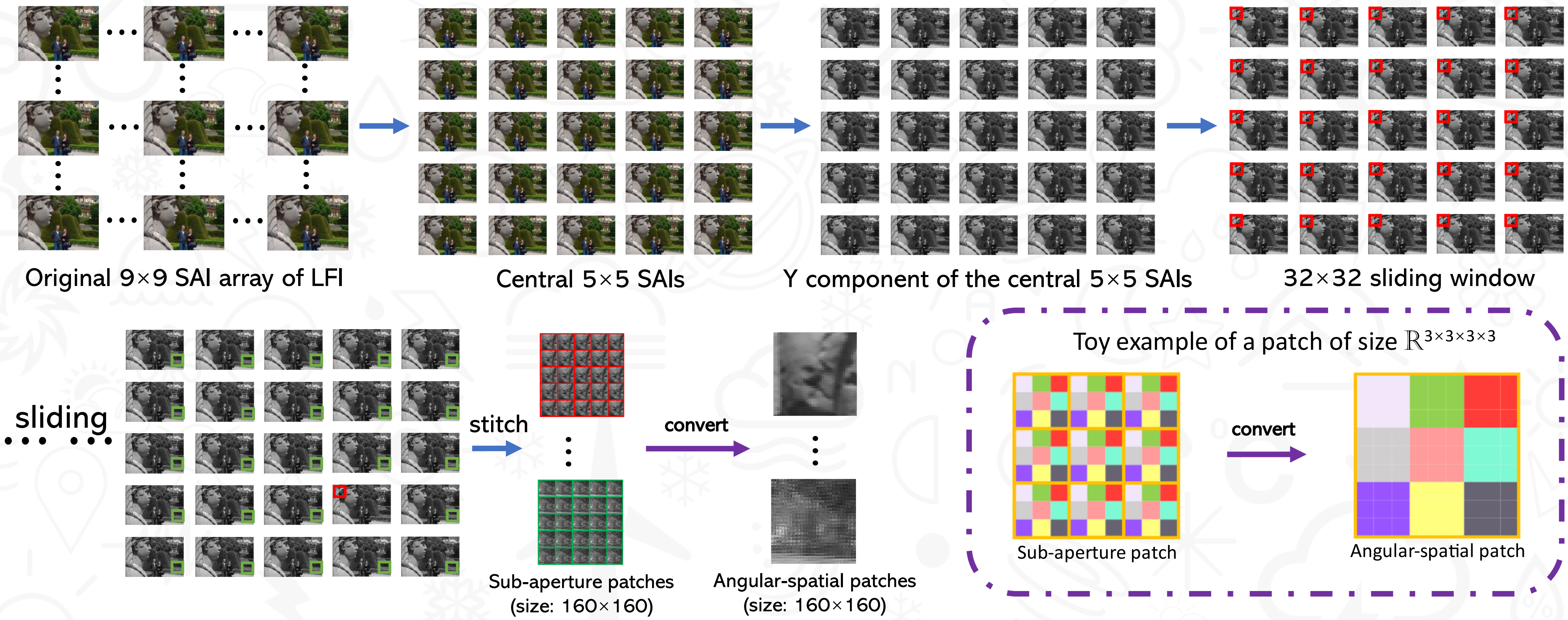
# Proposed Metric

## Deep Blind Light Field image quality assessment metric (DeeBLiF)



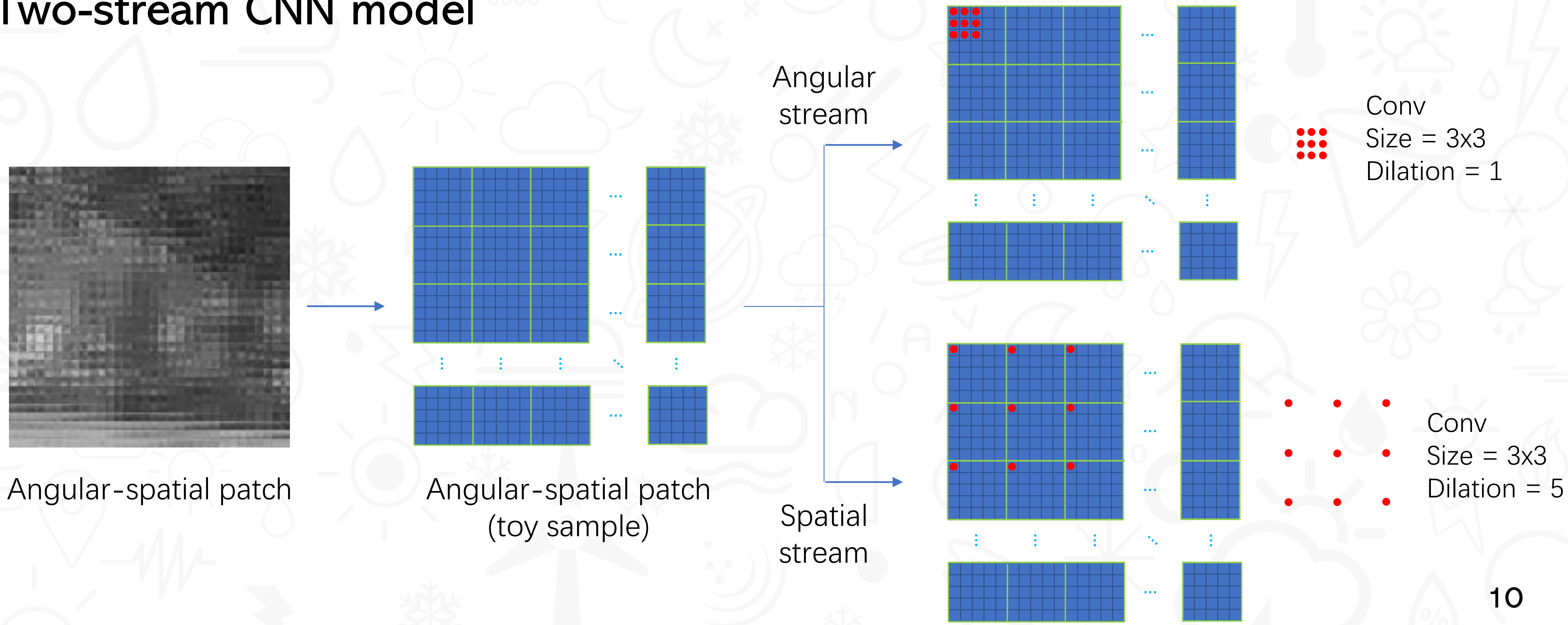
# Proposed Metric

## Angular-spatial patch generation



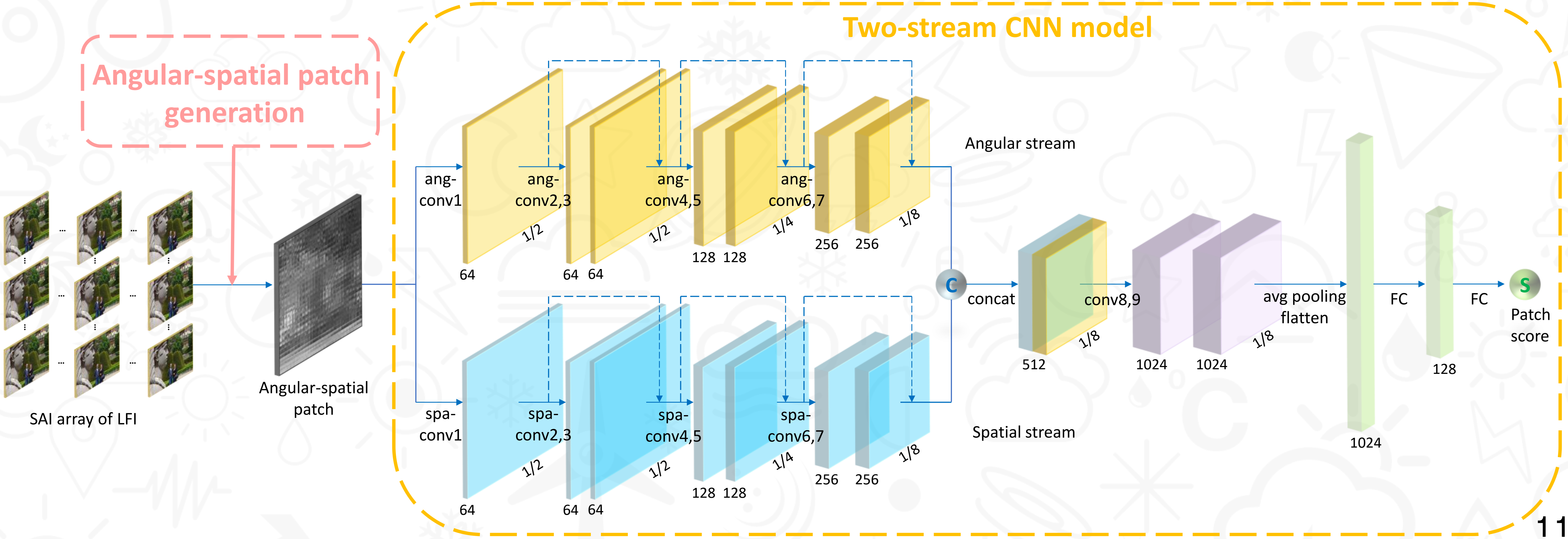
# Proposed Metric

## Two-stream CNN model



# Proposed Metric

## Two-stream CNN model



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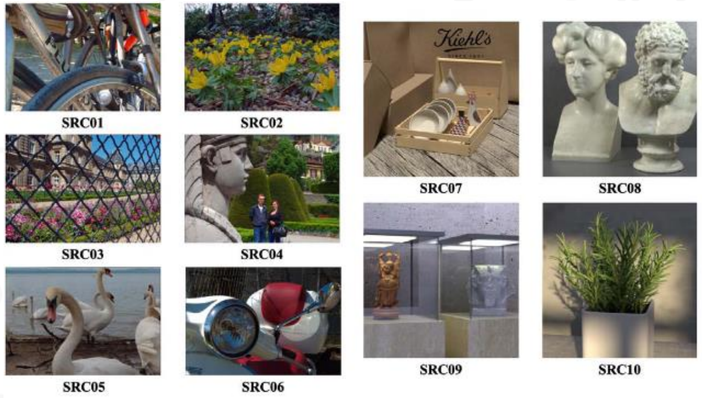
# Experiments

## Experimental settings

Dataset : Win5-LID dataset
(10 reference scenes and 220 distorted LFIs)

Training-test strategy : K-fold cross-validation
(K-2 folds for training and 2 folds for testing)

Evaluation criteria : Pearson Linear Correlation Coefficient (PLCC)
Spearman Rank Order Correlation Coefficient (SROCC)
Root Mean Square Error (RMSE)




All reference scenes in Win5-LID

# Experiments

## Results

**Table 1.** Overall performance comparison.

| Types | Metrics | PLCC↑ | SROCC↑ | RMSE↓ |
|---|---|---|---|---|
| NR 2D-IQA | BRISQUE | 0.5630 | 0.4547 | 0.7970 |
| | GWH-GLBP | 0.5768 | 0.3881 | 0.7820 |
| | NIQE | 0.5281 | 0.4403 | 0.8153 |
| NR 3D-IQA | SINQ | 0.5737 | 0.4039 | 0.7820 |
| NR Multi-view-IQA | MNSS | 0.3539 | 0.1844 | 0.9127 |
| | Wang's | 0.4295 | 0.2113 | 0.8745 |
| FR LF-IQA | MDFM | 0.7686 | 0.7337 | 0.6309 |
| | Min's | 0.7207 | 0.6429 | 0.6918 |
| NR LF-IQA | BELIF | 0.5912 | 0.5119 | 0.7572 |
| | VBLFI | 0.7042 | 0.6608 | 0.6819 |
| | NR-LFQA | 0.7297 | 0.6976 | 0.6270 |
| | Tensor-NLFQ | 0.7595 | 0.7345 | 0.6327 |
| | 4D-DCT-LFIQA | 0.8267 | 0.8079 | 0.5512 |
| | **DeeBLiF** | **0.8427** | **0.8186** | **0.5160** |

**Table 2.** Ablation study of different combinations of streams.

| Stream | PLCC↑ | SROCC↑ | RMSE↓ |
|---|---|---|---|
| angular | 0.8355 | 0.8088 | 0.5233 |
| spatial | 0.8224 | 0.7974 | 0.5440 |
| **two-stream** | **0.8427** | **0.8186** | **0.5160** |

From the TABLE:

1. The proposed DeeBLiF achieves the best performance.
2. Using both angular and spatial streams performs better than using a single stream.

# Conclusion

A novel patch-wise deep no-reference light field image quality assessment metric is proposed, which generates angular-spatial patches to address the problem of insufficient LFI training data. In addition, the proposed metric introduces a two-stream CNN model to fully extract the potential information in angular-spatial patches. Experimental results on the Win5-LID dataset demonstrate that the proposed metric outperforms the stat-of-the-art IQA metrics.


THANKS