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

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Outline

1. Introduction & Motivation
2. Proposed Metric
   - Overall framework
   - Angular-spatial patch generation
   - Two-stream CNN model
3. Experiments
   - Experimental settings
   - Results
4. Conclusion
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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
Introduction & Motivation

Introduction

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

Angular-spatial patch generation

Two-stream CNN model

Angular stream

Spatial stream

SAI array of LFI

Angular-spatial patch generation

Two-stream CNN model

Angular stream

Spatial stream

SAI array of LFI
Proposed Metric

Angular-spatial patch generation

Original 9×9 SAI array of LFI

Central 5×5 SAI

Y component of the central 5×5 SAI

32×32 sliding window

Sub-aperture patches
(size: 160×160)

Angular-spatial patches
(size: 160×160)

Toy example of a patch of size $R^{3\times3\times3}$

Sub-aperture patch

Angular-spatial patch
Proposed Metric

Two-stream CNN model

Angular-spatial patch

Angular-spatial patch (toy sample)

Angular stream

Spatial stream

Conv
Size = 3x3
Dilation = 1

Conv
Size = 3x3
Dilation = 5
Proposed Metric

Two-stream CNN model

Angular-spatial patch generation

SAI array of LFI
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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)
Experiments

Results

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.