

Four-Dimensional Sparse Filters for Near Real-Time Light Field Processing

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Declaration

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Abstract

Light is a fundamental form of conveying information. Sensing of light through conventional cameras leads to images and videos. In contrast to conventional images and videos, which capture only the directional variation of the intensity of light rays emanating from a scene, *light fields* capture the spatial variation as well. This richness of information has been exploited to accomplish novel tasks that are not possible with conventional images and videos, such as post-capture digital refocusing and depth filtering.

As a result of the massive data volume captured by a light field, the light field processing algorithms require higher memory and computational requirement. This is a major drawback for employing light fields in real-time applications. Hence, there is a need for investigating novel low-complexity light field processing algorithms that can be implemented in real-time applications. In this study, we address this critical research problem using multidimensional linear filter theory to develop novel low-complexity and sparse filters for light field processing. To this end, the work presented in this thesis focus on two major scenarios; light field denoising and volumetric refocusing. First, we present a novel low-complexity light field denoising algorithm, utilizing the sparsity of the region of support of a light field in the frequency domain. It turns out that the proposed filter runs in near real-time, compared to the previously reported light field denoising methods which take minutes. Next, a 4-D sparse filter for volumetric refocusing is presented. The proposed sparse filter provides 72% reduction of computational complexity compared to a non-sparse filter, with negligible distortion in fidelity.

Index terms— light field, Denoising, volumetric refocusing, real-time, sparse filters, low-complexity

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List of Abbreviations

1-D	One-Dimensional
2-D	Two-Dimensional
3-D	Three-Dimensional
4-D	Four-Dimensional
5-D	Five-Dimensional
7-D	Seven-Dimensional
AWGN	Additive White Gaussian Noise
BRDF	Bidirectional Reflectance Distribution Function
CDS	Correlated Double Sampling
CNN	Convolutional Neural Network
DFT	Discrete Fourier Transform
DOF	Depth of Field
EPI	Epipolar Plane Image
FFT	Fast Fourier Transform
FIR	Finite-Extent Impulse Response
FPGA	Field Programmable Gate Array
HT	Hard-Thresholding
IBR	Image-Based Rendering
iid	Independent and Identically Distributed
LF	Light Field
NRMSE	Normalized-Root-Mean-Square Error
PSNR	Peak-Signal-To-Noise Ratio
ROS	Region of Support
SAI	Sub-Aperture Image
SSIM	Structural Similarity

List of Algorithms

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