Advanced Deconvolution Techniques for High-fidelity Nanoscale 3D Printing

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Introduction

There is an exploding demand for fabricating complex three-dimensional (3D) structures with micro- and nanoscale features in various fields, including nanooptics, nanophotonics, microfluidics, and biomedicine. To expedite the fabrication process, digital light processing (DLP) is employed to print 3D objects in a layer-by-layer fashion. However, when the projected images take the form of non-periodic and more complex shapes, the light distribution across the focal plane becomes non-uniform due to the proximity effects of neighboring pixels. This leads to more intense light dosage in areas with more activated pixels and vice versa. This effect is particularly pronounced in the z-direction, causing over-curing and under-curing in different parts of the printed objects. Therefore, it is essential to apply algorithms to correct the projected image, ensuring that the light distribution is nearly uniform after optics. Richardson-Lucy (RL) deconvolution has been explored for such purposes, improving millimeter-scale volumetric 3D printing.[1] However, it does not provide the optimal solution for this type of inverse problem[2] and shows limited improvement for smaller scales (unpublished results). This project proposes a novel approach to mitigate this challenge by applying advanced image deconvolution techniques. Specifically, half quadratic splitting (HQS) and the alternating direction method of multipliers (ADMM) with different priors will be investigated to promote high-fidelity nanoscale printing.[3]

Methodology

1. **Data Collection**: Gather data on light intensity distribution from the actual printing setup to estimate point spread function for deconvolution.
2. **Deconvolution**: Implement the HQS and ADMM method to split the deconvolution problem into more manageable sub-problems, focusing on minimizing the discrepancy between the projected and desired light distributions. More importantly, different image priors will be investigated and nonnegativity constraints will be added.[4]
3. **Simulation**: Simulate the printing process using both the original and deconvolved projection images, analyzing the outcomes for quality improvements.
4. **Printing**: Evaluate the effectiveness of the proposed method by comparing the quality of 3D prints obtained with and without the deconvolution process.

Milestones

1. **Week 8**: Implement HQS and ADMM to 2D images for projection.
2. **Week 9**: Implement HQS and ADMM to 3D structures.
3. **Week 10**: Test deconvolution algorithm through real printing process.

References

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