Polarization Multi-Image Synthesis with Birefringent Metasurfaces

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Motivation: Computing with Sets of Images

All computational imaging tasks have benefited from the capture and processing of multiple images

- Images captured from the same perspective but with different optics
- Images captured from different viewpoints

https://www.optotune.com/machine-vision

Saragadam V. et al, Programmable Spectral Filter Arrays using Phase Spatial Light Modulators, arxiv 2021
Methods to capture multiple coded images in one exposure
Paradigm: Spectral filters as separate imaging channels

- Distinctly coded images on different wavelengths
- Mosaic of spectral filters at the sensor to retrieve set

(See also) A. Chakrabarti et al, ECCV 2012. (and) C. Corre et al., Journal of the Optical Society of America, 2015
Methods to capture multiple coded images in one exposure
New Paradigm: Polarization as imaging channels

Formalize and understand this type of architecture
1. Can we use all four polarization channels for imaging?
2. What are the capabilities of this system?

Snapshot **Polarization** Multi-Coded Imaging – New Opportunities
Creating the System with **Birefringent Metasurfaces**

Proposed metasurface-based architecture

Cell design theory (review)
Neural Representation for Gradient Based Optimization
Fundamental Channel Capacity -- Interference of Polarized Light

How many coded images can we design and measure with the polarization architecture?
How many coded images can we design and measure with the polarization architecture?

If we fix the intensity distributions $I_0, I_{90}$...
Can we control the intensities $I_{45}, I_{135}$ by optimizing the interference?

The Rigorous Answer: No...
- Specifying the intensity of light at the aperture and the sensor plane fixes its phase at both planes
The Practical Answer: Yes... if we compromise

- $I_0, I_{90}$: There are an infinite number of possible intensity patterns that approximate the target distribution
- Each one of these solutions has a different output phase → they can produce a different interference effect

Different approximations:
- Scattering light outside simulation region
- Error in matching intensity within the region

In computational imaging, we generally care about codes that enable reconstruction vs exact patterns (end-to-end optimization)
Motivations:

1) **Unsolved Hardware**: Compact and snapshot implementation of incoherent image processing for general scenes has not been achieved before.

→ Problem cannot be solved with spectral coding and required transition to polarization.
Applying the System: **Multi-Image Synthesis** Problem

Motivations:

1. **New Functionality**: Prior works synthesize a single optical filter for single depth or wavelength
   - Create synthesized filters with prescribed depth or wavelength dependence (sparse optical cues)
   - Implement multiple filters only by changing the summation weights
Task: Achieve different filtering operations only by changing the digital summation weights

Minimize loss based on the point-spread function (PSF)

Note: Regularization is Crucial!
1. Enforce light efficiency
2. Minimum Bias Factorizations
Multiple Filtered Images from a Single Exposure

Steerable Gaussian Derivatives

By changing the summation weights used to combine the four captured images, we can obtain the derivative along any orientation – at an absolute minimum computational cost.
Task: Orientation of the Gaussian derivative kernel to be dependent on object depth

Minimize loss based on the point-spread function (PSF)
Depth Dependent Derivatives

Different regions of the image have a different spatial frequency filter applied to it dependent on the depth map

- Synthesis requires only 3 FLOPs
- Difficult to produce equivalent image purely digitally
Task: Synthesize image filtering kernels with a prescribed wavelength dependence

End-to-end optimization using a loss computed on images

Target in paper: Wavelength invariant operation
- Simplest task that we are ensured is impossible to realize exactly
- Learn the closest synthesized filters that approximate our target operations
Engineering Synthesized Filters with Respect to Wavelength

Metasurfaces are dispersive

Each nanostructure has a different wavelength dependent phase
⇒ Ability to optimize and control the set of PSFs with respect to wavelength

Zero-Shot Generalization (Arad1k dataset)

Synthetic Target:

- $\lambda_1$
- $\lambda_2$
- $\lambda_3$
Validation of Design Theory with Prototype Camera

- Metasurface
- Off-the-shelf polarizer-mosaiced sensor
  - (Linear polarizer if we can’t assume unpolarized light)
  - (Spectral filter if we are testing single wavelength)
Conclusions and Future Remarks

Take-Aways:
• Metasurfaces excel at polarization (and wavelength) transformations
• Polarization, like wavelength, can be used as distinct multiplexed imaging channels
• Metasurfaces designed for multi-coded imaging can minimize/reduce computational costs

Future Remarks: Polarization and Spectral multi-coded systems are not mutually exclusive!
• Future systems can combine the two (metasurface is still ideal)
• Limitation of spatial resolution → Improved by smart demosaicing using learned statistical priors
• Optimize the capture of 16 distinctly coded images in a single snapshot
Open-source Auto-differentiable design framework (Tensorflow, Pytorch)

- Share metasurface cell libraries
- Pre-trained implicit Representations (MLP, ERBF, Multivariate-Poly)
- Field Propagation (Hankel + FFT; Angular Spectrum, Fresnel, Exact)
- Scene rendering operations (convolutional, noise)
- field solver (RCWA)

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Supplemental Slides
PSF decomposition as a constrained, non-negative matrix factorization problem:

\[ \text{argmin}_{H \geq 0, A} \| F - HA \|^2 \]

- The set of four PSFs (columns of \( H \)) are parameterized by metasurface \( \Pi \)
- Additional coupling by interference between different polarization channels
- Not all factorizations are equally useful in the presence of noise!

Filter-Target Objective

\[ \text{argmin}_{\alpha, \Pi} \sum_i \left( \frac{\| F^{(i)} - \frac{H\alpha^{(i)}}{\| H\alpha^{(i)} \|_2} \|^2}{\| F^{(i)} \|_2} + \mathcal{R} \right) \]

Image-Target Objective

\[ \text{argmin}_{\alpha, \Pi} \sum_i \left( \frac{\| F^{(i)} * I - \frac{(H * I)\alpha^{(i)}}{\| H\alpha^{(i)} \|_2} \|^2}{\| F^{(i)} \|_2} + \mathcal{R} \right) \]

Regularizer \( \mathcal{R} \):
1. Enforce light efficiency & the PSFs to be spatial compact
2. Minimum Bias Factorizations
Validation of the Cell Design Principle with Full Lens FDTD Simulations
Slide Variants