Progress report:

Optimization for 1D Scalar Grating Splitting 2 Beams

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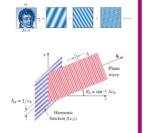
1 Scalar Fourier Optics

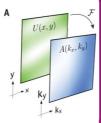
complex scalar transmittance function

$$U(x,y) = t(x,y)E_0(x,y)$$

plane wave expansion

$$\begin{cases} U(x,y) = \iint\limits_{-\infty}^{+\infty} A(k_x, k_y) e^{-i(k_x x + k_y y)} d\frac{k_x}{2\pi} d\frac{k_y}{2\pi} \\ A(k_x, k_y) = \iint\limits_{-\infty}^{+\infty} U(x, y) e^{i(k_x x + k_y y)} dx dy \end{cases}$$





- → xy coordinate space v.s. k wave vector space
- · requirements: paraxial incident

3 Matrix Fourier Optics

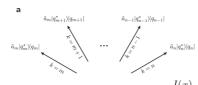
• special case 1: normal, uniform incident

$$\begin{split} \tilde{J}(\mathbf{x},\mathbf{y})|E_{0}(\mathbf{x},\mathbf{y})\rangle &\to \tilde{J}(\mathbf{x},\mathbf{y})|E_{0}\rangle \\ +\infty \\ \tilde{J}(\mathbf{x},\mathbf{y}) &= \iint\limits_{-\infty} \tilde{A}(\mathbf{k}_{x},\mathbf{k}_{y})e^{-i(\mathbf{k}_{x}x+\mathbf{k}_{y}y)}d\frac{\mathbf{k}_{x}}{2\pi}d\frac{\mathbf{k}_{y}}{2\pi} \\ +\infty \\ \tilde{A}(\mathbf{k}_{x},\mathbf{k}_{y}) &= \iint\limits_{-\infty} \tilde{J}(\mathbf{x},\mathbf{y})e^{i(\mathbf{k}_{x}x+\mathbf{k}_{y}y)}dxdy \\ \tilde{B} & \tilde{J}(\mathbf{x},\mathbf{y}) &= \int\limits_{-\infty} \tilde{J}(\mathbf{x},\mathbf{y})e^{i(\mathbf{k}_{x}x+\mathbf{k}_{y}y)}dxdy \\ & \tilde{J}_{\vec{k}} &= \int\limits_{-\infty} \tilde{J}(\mathbf{x},\mathbf{y})e^{i(\mathbf{k}_{x}x+\mathbf{k}_{y}y)}dxdy \\ &= \int\limits_{-\infty} \tilde{J}(\mathbf{x},\mathbf{y})e^{i(\mathbf{k}_{x}x+\mathbf{k}_{y}y)}dxdy \\ &= \int\limits_{-\infty} \tilde{J}(\mathbf{x},\mathbf{y})e$$

special case 2:

normal, uniform incident periodic grating

$$\begin{cases} \tilde{J}(x,y) = \sum_{\vec{k}} \tilde{J}_{\vec{k}} e^{-i(k_x x + k_y y)} \\ + \infty \\ \tilde{J}_{\vec{k}} = \iint_{-\infty} \tilde{J}(x,y) e^{i(k_x x + k_y y)} dx dy \end{cases}$$



2 Vector Fourier Optics

- Matrix transmittance function (**local Jones Matrix**) $\tilde{I}(x,y)$
- vector valued incident light (local Jones Vector) $|E_0(x,y)\rangle$ $|U(x,y)\rangle = \tilde{I}(x,y)|E_0(x,y)\rangle$
- plane wave expansion

$$\begin{cases} |U(x,y)\rangle = \tilde{J}(x,y)|E_0(x,y)\rangle = \int\limits_{-\infty}^{+\infty} |A(k_x,k_y)\rangle e^{-i(k_xx+k_yy)} d\frac{k_x}{2\pi} d\frac{k_y}{2\pi} \\ |A(k_x,k_y)\rangle = \int\limits_{-\infty}^{+\infty} \tilde{J}(x,y)|E_0(x,y)\rangle e^{i(k_xx+k_yy)} dxdy \end{cases}$$

requirements: paraxial incident

4 Beam Splitting → Parallel Polarization Analyzer

· multiplexing in k space: polarization analyzer

$$\tilde{J}(x,y) = \sum_{\vec{k} \in \{l\}} \tilde{J}_{\vec{k}} e^{-i(k_x x + k_y y)}, \quad \text{where} \quad \tilde{J}_{\vec{k}} = a_k |p_k\rangle\langle q_k|$$

realization in xy space: pp phase metasurface

$$\tilde{J}(x,y) = R(\theta(x,y)) \begin{bmatrix} e^{i\varphi_x(x,y)} & 0\\ 0 & e^{i\varphi_y(x,y)} \end{bmatrix} R(-\theta(x,y))$$

· conflict between two space:

can only **ideally** separate **conjugate polarized light**

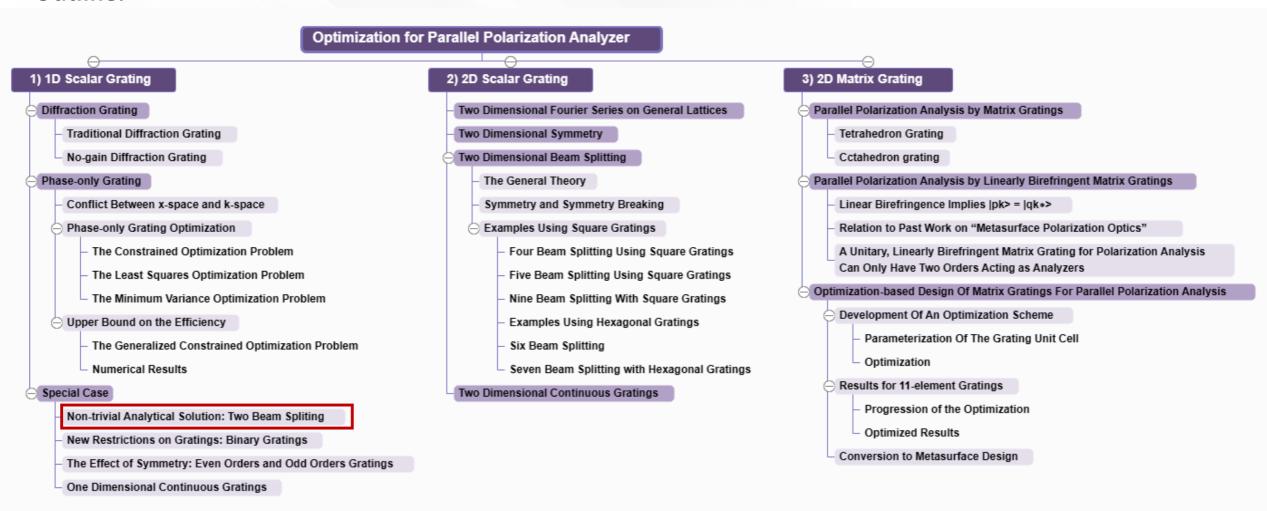
→allow light to leak into other orders







Outline:



Start from 1D scalar grating splitting 2 Beams, which has analytical optimization solution:

Optimization Problem Description:

Find the real 2π periodic function $\phi(x)$ such that we maximize the energy: $E = \frac{|a_1|^2 + |a_{-1}|^2}{\sum\limits_{k=-\infty}^{\infty} |a_k|^2}$

subject to the constraint that: $|a_1|^2 = |a_{-1}|^2$

where a_k are the Fourier coefficients of $e^{i\varphi(x)}$.

Theoretical Solution:

$$a_1 = a_{-1} = \frac{2}{\pi}$$
 $\eta = |a_1|^2 + |a_{-1}|^2 = \frac{8}{\pi^2} \approx .8106$

Reference:

Gori, F. (1997). Diffractive optics: An introduction. In S. Martellucci, & A. N. Chester (Eds.), Diffractive optics and optical microsystems. New York: Plenum.



My code and idea:

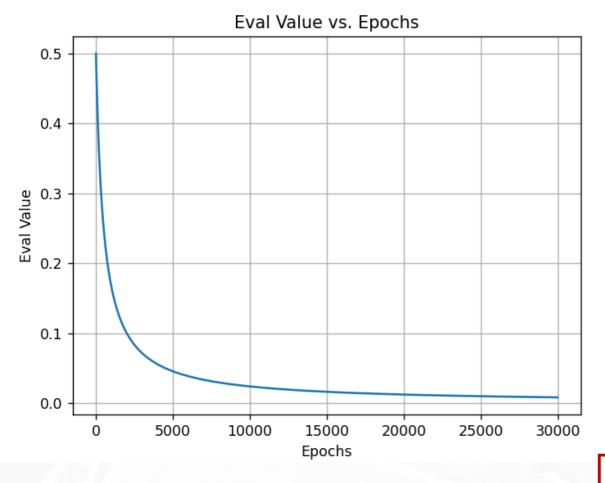
```
import numpy as np
import torch
import matplotlib.pyplot as plt
                                                         # take period=2pi for convenience, it doesn't affect Fourier coefficients
x_{values} = np.linspace(-np.pi, np.pi, 10000)
p_values = x_values
                                                         # 1D Torch.tensor "p" describes phase function \phi(x)
x = torch.tensor(x_values, dtype=torch.float32)
p = torch.tensor(p_values, dtype=torch.complex64)
p.requires_grad = True
def compute_fourier_coefficients(p, x):
                                                         # FFT calculates coefficients
   f_x = torch.exp(1j * p)
   N = len(x)
   coefficients = torch.fft.fft(f_x) / N
   return coefficients
def energy_efficiency(coefficients):
                                                                                                      # energy efficiency: E = \frac{|a_1|^2 + |a_{-1}|^2}{\sum_{k=0}^{\infty} |a_k|^2}
   total_energy = torch.sum(torch.abs(coefficients)**2)
   abs_square_coefficient_pos1 = torch.abs(coefficients[1])**2
   abs_square_coefficient_neg1 = torch.abs(coefficients[-1])**2
   efficiency_ratio = (abs_square_coefficient_pos1 + abs_square_coefficient_neq1) / total_energy
   return efficiency_ratio
def eval(coefficients, alpha=0.5):
   abs_square_coefficient_pos1 = torch.abs(coefficients[1])**2
                                                                                                      # eval function:
   abs_square_coefficient_neg1 = torch.abs(coefficients[-1])**2
   balance_term = abs(abs_square_coefficient_pos1 - abs_square_coefficient_neg1)
                                                                                                       (1-\alpha)(1-E)+\alpha(|a|1|^2-|a|-1|^2)
   return (1 - alpha) * (1 - energy_efficiency(coefficients)) + alpha * balance_term
```



My code and idea:

```
learning_rate = 2.0
                                                              # Pytorch grad descent
eval_values = []
for epoch in range(30000):
   coefficients = compute_fourier_coefficients(p, x)
   e = eval(coefficients)
    e.backward()
   eval_values.append(e.item()) # Save the eval value
   with torch.no_grad():
       p -= learning_rate * p.grad
       p.grad.zero_()
   if epoch % 100 == 0: # Print every 100 epochs
       print('Epoch:', epoch, 'Eval:', e.item())
print("Result:", p)
coefficients = compute_fourier_coefficients(p, x)
                                                              # Output and Plot
abs_square_coefficient_pos1 = torch.abs(coefficients[1])**2
abs_square_coefficient_neg1 = torch.abs(coefficients[-1])**2
print("coefficient_pos1:", abs_square_coefficient_pos1)
print("coefficient_neg1:", abs_square_coefficient_neg1)
print("energy_efficiency:", energy_efficiency(coefficients))
plt.plot(eval_values)
plt.xlabel('Epochs')
plt.ylabel('Eval Value')
plt.title('Eval Value vs. Epochs')
plt.grid(True)
plt.show()
```

Result:



Epoch: 27400 Eval: 0.008959934115409851 Epoch: 27500 Eval: 0.008927948772907257 Epoch: 27600 Eval: 0.008896077051758766 Epoch: 27700 Eval: 0.008864541538059711 Epoch: 27800 Eval: 0.008833317086100578 Epoch: 27900 Eval: 0.008802201598882675 Epoch: 28000 Eval: 0.00877120066434145 Epoch: 28100 Eval: 0.008740590885281563 Epoch: 28200 Eval: 0.008710218593478203 Epoch: 28300 Eval: 0.008679949678480625 Epoch: 28400 Eval: 0.008649789728224277 Epoch: 28500 Eval: 0.008620046079158783 Epoch: 28600 Eval: 0.008590501733124256 Epoch: 28700 Eval: 0.008561057969927788 Epoch: 28800 Eval: 0.008531716652214527 Epoch: 28900 Eval: 0.00850276742130518 Epoch: 29000 Eval: 0.008474026806652546 Epoch: 29100 Eval: 0.008445384912192822 Epoch: 29200 Eval: 0.008416841737926006 Epoch: 29300 Eval: 0.00838861707597971

Epoch: 29400 Eval: 0.0083606643602252

Epoch: 29500 Eval: 0.008332801051437855 Epoch: 29600 Eval: 0.008305035531520844 Epoch: 29700 Eval: 0.008277468383312225 Epoch: 29800 Eval: 0.008250277489423752

Epoch: 29900 Eval: 0.008223176002502441

eval function:

$$(1-\alpha)(1-E)+\alpha(|a_1|^2-|a_-1|^2)$$

where
$$E = \frac{|a_1|^2 + |a_{-1}|^2}{\sum_{k=-\infty}^{\infty} |a_k|^2}$$

Theoretical Solution:

$$a_1 = a_{-1} = \frac{2}{\pi}$$

Result: tensor([-3.1414+2.0552j, -3.1408+2.0552j, -3.1401+2.0552j, ...,

3.1401+2.0552i. 3.1408+2.0552i. 3.1414+2.0552il. requires_grad=True)

coefficient_pos1: tensor(0.0164, grad_fn=<PowBackward0>)
coefficient_neg1: tensor(1.2752e-09, grad_fn=<PowBackward0>

energy_efficiency: tensor(1., grad_fn=<DivBackward0>)

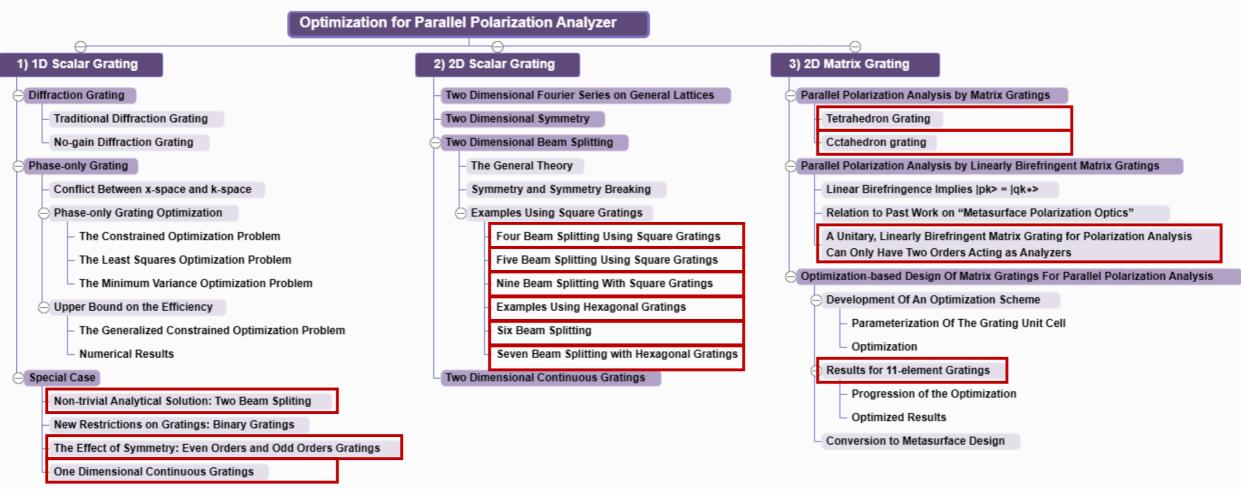


Reason may come from:

Improper weight factor of eval function, Using torch.fft.fft incorrectly, Error in grad descent, Bad initial value



Follow-up Plan:



In Pytorch: parameters to be determined:

1D Tensor 2D Tensor

Red boxes: important examples I want to replicate

4 * 2D Tensor