A Regularized Optimization Approach for Optogenetic Stimulation using Ferroelectric SLMs*

Dimitris Ampeliotis[a,b], Christina (Tanya) Politi[c], Aggeliki Anastasiou[b], and Dimitris Alexandropoulos[b]

[a]Department of Digital Media and Communication, Ionian University, Greece
[b]Department of Materials Science, University of Patras, Rio, Patra, Greece
[c]Department of Electrical and Computer Engineering, University of Peloponnese, Greece

ABSTRACT

In this work, the problem of designing proper Phase-Shifting Masks (PSMs) suitable for optogenetic applications is considered. In such applications, structured light is used to stimulate neurons or groups of neurons while short-term excitation is required to study the dynamics of the neuronal activity. In practice, such fast response times can be achieved only via the use of ferroelectric Spatial Light Modulators (fSLMs) that posses significantly smaller response times as compared to the, more common, liquid crystal based SLMs. However, typical fSLMs are restricted to using only a small number of discrete phase levels. To this end, we propose a regularized cost function for Phase-Shifting Mask design, that promotes phases in a discrete phase set. Significantly higher Peak Signal-to-Noise Ratio (PSNR) is achieved by the proposed approach, as compared to other approaches.

Keywords: Optogenetics, discrete levels phase shifting mask design,ferroelectric SLMs

1. INTRODUCTION

The field of optogenetics studies the targeted light stimulation of neurons that have been previously functionalized with light-sensitive compounds, called opsins.[1] Due to the prospects that it offers for specified neuronal stimulation, the field of optogenetics has been embraced by the research community as an efficient tool towards demystifying the operation of the brain.[2] Indeed, the optogenetic method has the potential of stimulating a complex of neurons down to a single neuron. This unprecedented specificity and spatial flexibility cannot be matched by other deep brain stimulation techniques. Furthermore, in many studies, short-term excitation is required to study the dynamics of the neuronal activity, since the impulse response function of networks is best obtained with spatiotemporally well-defined stimuli. In practice, such fast response times can be achieved only via the use of fSLMs.[3] However, typical fSLMs are restricted to using only a small number of discrete phase levels, most commonly two or four, where in the latter case, two binary fSLMs are employed.[4]

To this end, it is becoming important to device methods that design accurate computer-generated holograms, using discrete level phase shifting masks. Previous works on this problem have mainly focused on lithography applications. In particular, the work[5] presents a comparative study of various cost functions employed for designing phase shifting masks in lithography applications. Also, in,[6] the authors propose a regularized optimization approach to tackle various practical problems that arise in lithography. More recently, researchers have proposed[7] an innovation to the so-called error diffusion algorithm. Also, in,[8] the authors employ deep learning for reducing the computational complexity of the phase design process.

While most previous works for the problem of discrete-level phase shifting mask design have mainly considered lithography applications, in this work the focus is on the application of optogenetics. Extending the approach adopted in,[6] in this work we propose a new cost function for this problem, that comprises of a mean squared

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Further author information: Send correspondence to Dimitris Alexandropoulos, E-mail: dalexa@upatras.gr, Telephone: (+30) 2610 996304

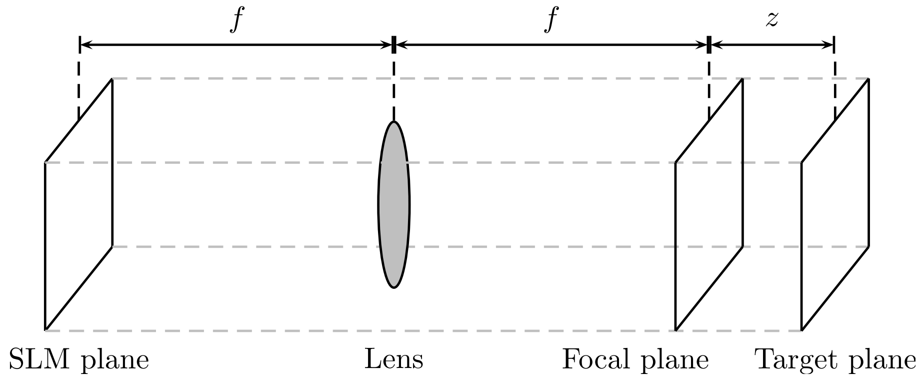


Figure 1. The optical path considered

error (MSE) fidelity term plus a proper sinusoidal regularization part. The regularization part penalizes phase values that are away from the desired discrete phase levels, while having zero value at all phase levels that can be represented.

2. THE PROPOSED APPROACH

Let us consider that the input phase mask is denoted as $\phi(x,y)$, where $x, y \in \{1, 2, \dots, N\}$ denote the discrete space coordinates (pixels) on the SLM plane. We consider that $\phi(x,y)$ is not allowed to take any value in $\mathbb{R}$, rather, only q equidistant phases are permitted, as denoted by

$$\phi(x,y) \in \Phi = \left\{ k \cdot \frac{2\pi}{q} : k \in \mathbb{Z} \right\} \ , \tag{1}$$

where q denotes the number of discrete phase levels, typically 2 or 4 for the considered application, and Φ is the corresponding set of permissible phase values. We assume that monochromatic light from a proper laser source is reflected by the SLM device, thus generating the (input) light field

$$I(x,y) = A \cdot \exp\left(j \cdot \phi(x,y)\right), \quad x, y \in \{1, 2, \dots, N\} \ , \tag{2}$$

where $A \in \mathbb{R}^+$ denotes the intensity of the input light field and j denotes the complex imaginary unit, that is $j^2 = -1$. We also consider that $I(x,y)$ is the input to an optical system that generates the output light field $O(x,y) \in \mathbb{C}$, as described by the relation

$$O(x,y) = H\left(I(x,y)\right) = H\left(A \cdot \exp\left(j \cdot \phi(x,y)\right)\right) \ , \tag{3}$$

where the function $H(\cdot)$ describes the optical system under study. As an example, for lithography applications, $H(\cdot)$ is usually modeled as a low-pass Gaussian filter followed by an operation that computes the magnitude of the complex light field and the application of a sigmoid function.[6] In this work, we consider the optical path demonstrated in Figure 1, that consists of a 2f setup with focal length f followed by free space propagation at a distance z. Since our focus is on an optogenetics application, the parameters of our simulation setup were selected so that the field-of-view at the target plane is an area of 266×266 μm.

Clearly, the output light field $O(x,y)$ is a function of the input light amplitude A and the phases $\phi(x,y)$. Given a *desired response* output intensity field $D(x,y) \in \mathbb{R}^+$, the optimal values A^* and $\phi^*(x,y)$ for the parameters A and $\phi(x,y)$ are given as the solution to the following optimization problem

$$\{A^*, \phi^*(x,y)\} = \arg \min_{A \in \mathbb{R}^+, \phi(x,y) \in \Phi} \left(d\left(\left| H\left(A \cdot \exp\left(j \cdot \phi(x,y)\right)\right)\right|^2, D(x,y) \right) \right) \ , \tag{4}$$

where $d(\cdot,\cdot)$ denotes some suitable distance/cost function, for example, the mean square error (MSE) or any other, more elaborate, cost function as in.[9] It is easily seen that problem (4) is a combinatorial optimization

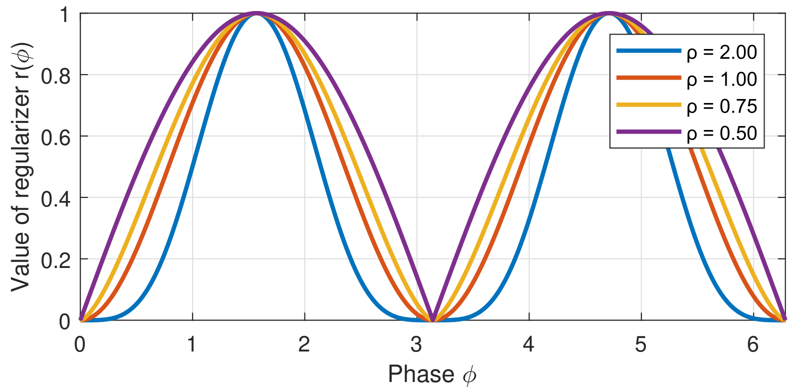


Figure 2. The shape of the proposed regularization term for $\lambda = 1$, $q = 2$ and various values for the exponent ρ

problem in the sense that the optimal solution can be obtained by examining all q^{N^2} possible phase shifting masks and finding the one that yields the minimum cost, while the problem gets complicated even more due to the continuous variable A. Thus, in practice, the optimal solution of (4) cannot be computed. A simple approach to circumvent this problem, and derive a sub-optimal solution, is to solve (4) by neglecting the constraint $\phi(x, y) \in \Phi$, letting $\phi(x, y) \in \mathbb{R}$, and then to replace each of the resulting phase values by the closest phase level from the constraint set Φ. In the sequel, we refer to this approach as *quantization*.

Trying to solve (4) while neglecting the constraint $\phi(x, y) \in \Phi$ makes the problem significantly easier, however, the resulting solution (after quantization) exhibits poor performance, in the sense that the resulting output intensity $|O(x, y)|^2$ will be significantly different from the desired intensity $D(x, y)$. To circumvent this effect, we employ the notion of regularized optimization. In essence, the method utilizes a modified cost function by adding a proper regularization part that penalizes values of the variables that do not satisfy the initial constraint. To this end, in this work we propose to use the cost function

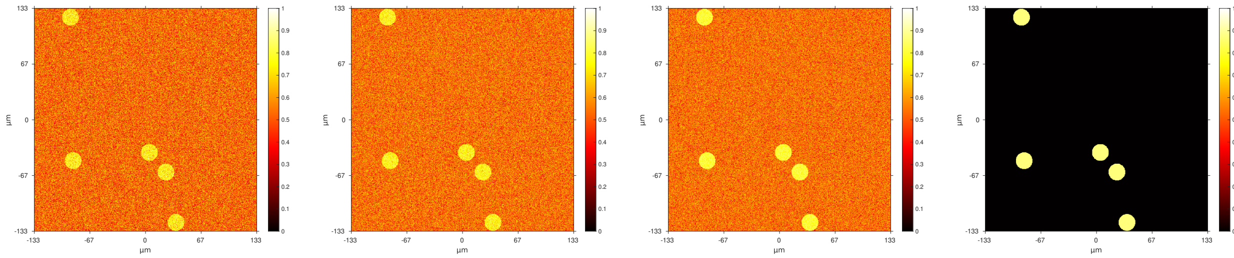
$$d\left(|O(x,y)|^2, D(x,y)\right) = \frac{1}{N^2}\sum_{x=1}^{N}\sum_{y=1}^{N}\left(|O(x,y)|^2 - D(x,y)\right)^2 + \frac{1}{N^2}\sum_{x=1}^{N}\sum_{y=1}^{N}\frac{\lambda}{2^\rho}\left(\sin\left(q\cdot\phi(x,y) + \frac{3\pi}{2}\right) + 1\right)^\rho \quad (5)$$

which consists of a first term that is recognized as the MSE between $|O(x, y)|^2$ and $D(x, y)$ and a second regularization part that is the average of some regularization terms that are non-negative, obtain zero value only when $\phi(x, y) = k \cdot 2\pi/q, k \in \mathbb{Z}$, and penalize phase values that are away from the values in Φ. The parameter λ controls the relative importance between the fidelity term (MSE) and the regularization part. Also, the parameter ρ controls the shape of the regularization terms. In Figure 2 we have plotted one regularization term for $\lambda = 1$, $q = 2$ and various values for ρ, as a function of the variable $\phi(x, y)$ in the interval $[0, 2\pi)$. We can see from Figure 2 the the regularization term becomes zero only for $\phi(x, y) = k \cdot \pi$, $k \in \mathbb{Z}$, its maximum value is equal to $\lambda = 1$ and the parameter ρ controls the shape of the function. It is easy to verify that the regularization term becomes non-smooth when $\rho < 1$. It should be noted that a similar regularization part has been proposed,[6] however, the authors only considered the case where $\rho = 2$. In this work, we demonstrate that values for $\rho < 2$ are preferable, if the non-smoothness of the regularization part is properly tackled.

Since the cost function in (5) becomes non-smooth for $\rho < 1$, we employ suitable optimization methods for such functions. Among various methods, the subgradient method[10] and the so-called proximal algorithms[11] are the most successful. In this work, we utilize a subgradient method, while future work will focus on the application of proximal algorithms.

3. NUMERICAL RESULTS

In this section the results of our study are demonstrated. The simulation setup and parameters used were as follows: A square 512×512 SLM device, measuring $1,024$ cm along each dimension, was considered. We used monochromatic light with $\lambda = 532$ nm. The light reflected by the SLM travels through a 2f setup with focal



(a) (b) (c) (d)

Figure 3. Demonstration of the resulting images (where the fifth root of the intensities, multiplied by 1/2, have been used to amplify the details) (a) after simple quantization to 2 levels, (b) using $\rho = 2, \lambda = 0.007, q = 2$ followed by quantization (approach from[6]), (c) using $\rho = 0.5, \lambda = 0.035, q = 2$ followed by quantization (proposed approach), (d) desired response intensity image

length $f = 10$ cm. In the sequel, for the scopes of reducing the considered pixel size, we consider free space propagation of the light along a distance equal to 1 cm, using a two step Frenel propagation method and a magnification parameter $m = 1/10$.[12] Thus, we arrive to a pixel size of around $dx = 0,52$ μm at the target plane (see Figure 1).

Since we are considering an optogenetics application, the desired response intensity image $D(x, y)$ was created as five, randomly placed, disks with a radius equal to 10 μm, as it is demonstrated in Figure 3.(d), where each disk corresponds to the approximate size and shape of a neuronal soma in the mouse cerebral cortex.[9] We compare the performance of the proposed method against the simple phase quantization method and the approach with $\rho = 2$, that has appeared in previous works.[6] The methods are compared in terms of the Peak Signal-to-Noise Ratio (PSNR), defined in terms of the MSE as

$$PSNR = 10 \log_{10} \left(\frac{\max_{x,y} \left(D(x,y)^2 \right)}{MSE} \right) , \tag{6}$$

where the maximum value of the desired response intensity was $\max_{x,y} \left(D(x,y)^2 \right) = 1$, and the MSE is defined as

$$MSE = \frac{1}{N^2} \sum_{x=1}^{N} \sum_{y=1}^{N} \left(|O(x,y)|^2 - D(x,y) \right)^2 \tag{7}$$

The results obtained can be seen in Table 1. It is evident from these results that the proposed approach offers significant performance improvements against a simple phase quantization approach as well as against a previously reported method.[6] In particular, for $q = 2$, the proposed approach offers more than 1.5 dB better performance as compared to the simple phase quantization approach, and 1 dB better performance as compared to the previous method. For $q = 4$, the proposed approach offers more than 1 dB better performance as compared to the simple phase quantization approach, and more than 0.5 dB as compared to the previously reported approach.[6] Note that for the proposed approach as well as for the previously reported approach, several experiments were conducted to yield the best values for the parameters λ and ρ, and these values also appear in Table 1. Also, some resulting images for the approaches considered can be seen in Figure 3.

Table 1. Numerical results for various approaches in terms of the PSNR obtained

	Quantization	$\rho = 2$ (Approach in[6])	Proposed Approach
$q = 2$	14.8 dB	15.4 dB ($\lambda = 0.007$)	16.4 dB ($\lambda = 0.035, \rho = 0.5$)
$q = 4$	17.5 dB	18.0 dB ($\lambda = 0.003$)	18.6 dB ($\lambda = 0.010, \rho = 0.5$)

4. CONCLUSIONS

In this work, the problem of discrete level phase mask design was considered, in the context of neural photostimulation employing fast ferroelectric SLMs. A regularized cost function was proposed for this problem and it was demonstrated that this approach offers some performance benefits against approaches previously reported. The new cost function considered here is non-smooth, thus the subgradient optimization approach was employed to yield a solution. Future work will focus on a more detailed performance comparison against other methods as well as on the application of proximal optimization algorithms.

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