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Diffractive neural networks as a tool for three-dimensional beam shaping in laser materials processing

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Abstract

Diffractive neural networks are a design method for cascading diffractive optical elements or spatial light modulators that is based on neural network training techniques. In previous work, we have shown that these systems can be used for complex beam shaping tasks like combined beam splitting and shaping, high depth-of-focus through simultaneous optimization of amplitude and phase and the shaping of multiple target planes for effective 3D profiles. Additionally, alignment errors can be addressed and compensated during training and other optical elements like lenses can be included into training without effort.
Here, we present the method, advantages compared to other beam shaping techniques and applications in laser materials processing like for example in surface treatment.

Keywords: beam shaping, artificial intelligence, spatial light modulator, diffractive optics

1. Introduction

In laser materials processing, the intensity distribution of the laser beam on the work piece significantly affects the quality and productivity of the processes (Annika Völl et al. 2018). Apart from the conventional Gaussian beam profile, alternative intensity distributions such as uniform top-hat distributions, donut shapes, or other complex distributions are chosen. Achieving these specific distributions necessitates the utilization of advanced beam shaping methods, including systems comprised of spherical and aspherical lenses and mirrors, freeform optics, diffractive optical elements (DOEs), or spatial light modulators (SLMs) like Liquid Crystal on Silicon (LCOS-SLM) (Fred M. Dickey et al. 2000).

Although these methods offer excellent beam shaping capabilities in a two-dimensional target plane, their effectiveness is limited beyond this single plane. Especially when working with transparent materials or non-planar surfaces, shaping the intensity distribution in a three-dimensional space can be advantageous or even necessary. In previous works, great results have been made with Bessel-like beams (Daniel Flamm et al. 2019) or using two phase masks where the second phase masks corrects the phase of a field using analytical solutions for the mask design (Lisa Ackermann et al. 2021). Recently, we have proposed Diffractive Neural Networks (DNNs) as a versatile tool for realizing three-dimensional beam shaping (Paul Buske et al. 2022). DNNs represent a physical implementation of artificial neural networks that employ light as the information, while phase masks serve as the network's layers. Each pixel within each layer, i.e. in each phase mask, functions as a neuron in this network which is connected to the neurons in each previous and subsequent layer through optical propagation. DNNs can be trained in a computer to accomplish specific tasks and after training, the calculated diffractive layers can be realized with phase masks. Originally motivated for enabling image processing at the speed of light (Xing Lin et al. 2018), DNNs can also be utilized for laser beam shaping. Our design algorithm for the DNNs offers several advantageous features for beam shaping:

- Shaping of both amplitude and phase: The phase of the field can be adjusted as an additional optimization objective for e.g. increased depth-of-focus.
- Multiple simultaneous target planes: By optimizing not only for one target plane but for multiple planes, effective three-dimensional beam shaping becomes achievable.
- Robustness against misalignment: As initially outlined in (Jiashuo Shi et al. 2021), the training can be performed by incorporating variations of the input beam, such as lateral shifts or deviations in beam radius. Consequently, the calculated optical system automatically becomes robust against these deviations. Alignment errors of the phase masks can also be addressed as described in (Deniz Mengu et al. 2020) for image processing DNNs.

Furthermore, other optical components like lenses or mirrors can be included in the training process as static elements. This is very convenient for small target distributions, as e.g. lenses help reduce the necessary refractive power of the phase masks for simplifying fabrication. Additionally, since the used AI training algorithms natively use GPUs, training of a DNN for beam shaping only takes a few minutes. In the following, we show experimental results of DNNs based on SLMs and we outline two approaches for enabling three-dimensional beam shaping for laser materials processing.

2. Results

2.1. Example experiments

DNNs can be realized by various kinds of phase mask, like DOEs, SLMs or meta-optics. While each implementation has its advantages and disadvantages, we employed SLMs using Liquid Crystal on Silicon (LCoS) for demonstrating the results (Maxson et al. 2014). This is convenient because they can be addressed dynamically and used for various DNN configurations in the same setup. For a high-power application with static beam shaping the LCoS can be replaced with DOEs. Our setup uses a 50 µW, 633 nm HeNe laser that is linearly polarized as required for the SLMs. We use up to two cascaded Hamamatsu SLMs of the type X15213-13 with 1024 x 1272 controllable pixels and a pixel pitch of 12.5 µm.

We present an example for experimental beam shaping using one SLM in 250 mm distance and two SLMs including phase optimization with 250 mm distance between the SLMs (Figure 1). Both setups perform their respective task with high accuracy, with the intensity distributions of the two-layer network being slightly less sharp but more homogeneous. Additionally, as for the two-layer network the phase is designed to be constant in the target plane, the effective depth-of-focus is increased. The results demonstrate that our approach is not only theoretically viable but also experimentally.

2.2. Applications in laser materials processing

We show two examples on how a two-layer DNN is used in two different ways for increasing the depth-of-focus in laser materials processing. Both examples are simulated assuming a 1064 nm laser as input beam. Each layer could be experimentally implemented with an SLM that has at least 1024 x 1272 pixels with a pixel pitch of 12.5 µm and can be applied for the chosen wavelength. The beam diameter of the Gaussian input beam is set to 5.3 mm. In the training examples with two layers, the layers are separated by 250 mm.

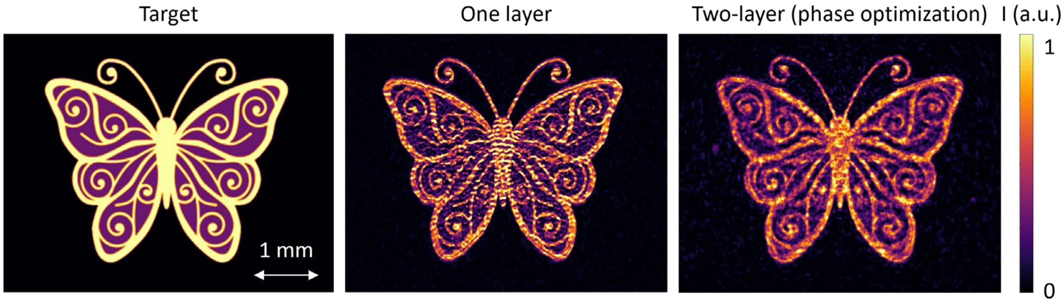

Fig. 1. Example experimental results for DNNs with both a single-layer and a two-layer network.

The armchair intensity distribution (Figure 2) can be used to achieve a homogeneous temperature profile in the laser hardening process (Annika Völl et al. 2018). This intensity distribution exhibits an edge length of 3 mm. As it is a quite large and smooth distribution, it can be considered effectively collimated in the target plane when the phase remains constant. We train a two-layer DNN to achieve this armchair distribution with constant phase at 200 mm measured from the second SLM. The result is compared to a single SLM that is trained without phase optimization for the same target distance to show the difference in the depth-of-focus.

The simulated intensity distributions of both configurations and varying distances are depicted in Figure 3.

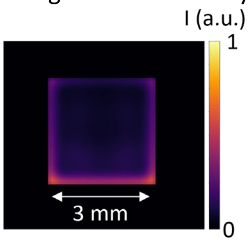

Figure 2: Armchair intensity distribution, which serves as the target distribution for the optimization.

In the top row the “conventional” result of a single SLM is shown, while in the bottom row the two-layer DNN is shown. While for both configurations the target intensity distribution is obtained at the target distance, it is obvious that the two-layer DNN approximates the desired intensity distribution also both 20 mm before and after the target plane. This could be used in a hardening process of a surface with different height levels without needing to reposition the laser.

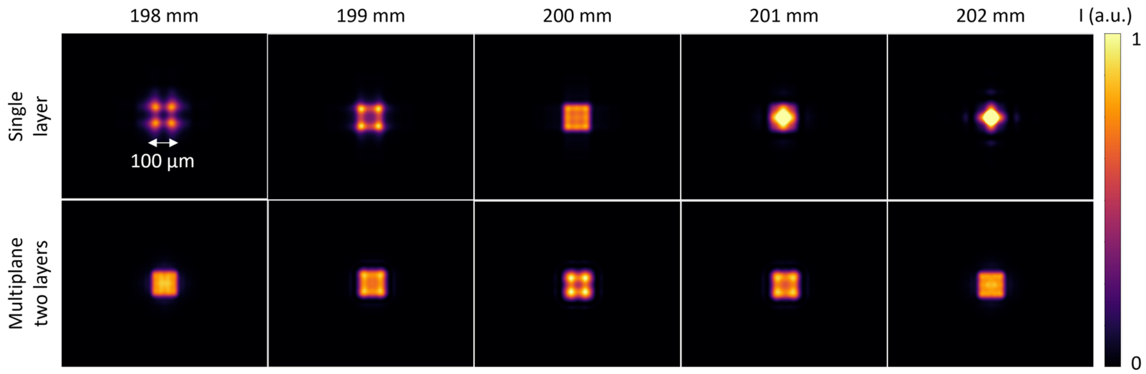

Figure 4: Comparison of depth-of-focus for small target distributions: Top: Single SLM with one target plane. Bottom: Two SLMs with five target planes.

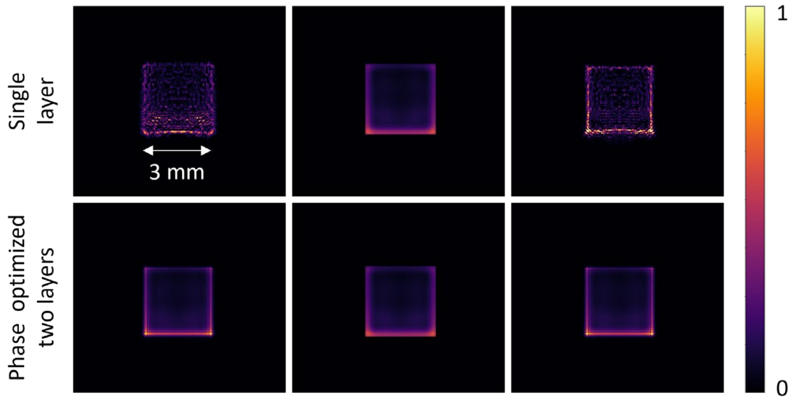

Figure 3: Comparison of depth-of-focus for large target distributions: Top: Single SLM with one target plane. Bottom: Two SLMs with one target plane and constant phase optimization.

As a second example, a square top-hat distribution with an edge length of 100 µm is investigated. This distribution is too small to fully benefit from phase optimization as it would diffract too much when propagating away from the target plane. Instead, we set five different target planes in distance steps of 1 mm that all shall achieve the same intensity distribution. The distance between planes must be chosen small enough to ensure that the beam does not change its shape between the planes. A higher density of planes results in more reliable training results but also increases the computational cost. In this example we did not limit the setup to two SLMs but also included an ideal focusing lens with f = 200 mm behind the second SLM in the training to reduce the refractive power otherwise needed from the SLMs. As the center target plane, we choose the focal plane of this lens. The simulated intensity distributions in various distances are shown in Figure 4: In the top row, the results of a single SLM without multiple target planes are shown, in the bottom row the corresponding results for a two-layer network with five target planes are depicted. The five shown planes are also the respective planes that were optimized for. While in the focal plane itself, the top-hat distribution is created more accurately in the single SLM setup, in all other distances the two-layer network preserves the shape more clearly. This demonstrates that even for small intensity distributions, DNNs can increase the effective depth-of-focus.

3. Summary and Outlook

In summary, DNNs are a valuable concept for application-adapted beam shaping in laser materials processing. They can be used not only for arbitrary phase mask design with single phase masks but also for cascading phase masks enabling advanced features like a higher depth-of-focus for small and large intensity distributions. We have presented theoretical results and the experimental demonstration of one- and two-layer networks with spatial light modulators. In the next steps, we perform an experimental tolerancing analysis for different alignment parameters and increase the robustness against the variations in the training procedure. We also develop an ultra-short pulse laser processing machine including multiple SLMs and monitoring systems all controlled with a microservice architecture. This setup allows for adaptive beam shaping by utilizing an intelligent digital twin of the complex optical system, which employs the presented DNN design method to compute phase masks on demand.

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