Autonomous and Self-correcting Laser Subtractive Patterning Using Reinforcement Learning

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Abstract: A novel subtractive laser patterning approach, actuated by reinforcement learning-controlled motorized XYZ stages, enables path-planning for quasi-arbitrary target patterns and an ability to supervise the machining process and perform self-correction following inadvertent pulse misfires.

Laser patterning enables micro- and nano-scale additive and subtractive material structuring. It commonly involves movements of motorized stages (e.g., linear or rotary stages) or beam-delivering optics (e.g., galvanometer scanning mirrors), and in some cases, it also incorporates beam shaping devices, for instance, spatial light modulators (e.g., digital micromirror devices (DMD)). The steering of the moveable apparatus often relies heavily on manual labor in terms of toolpath design, and the process of patterning is usually unforgiving in the sense that any unintended and unwanted incident laser pulses may result in a defective product. In this manuscript, a novel laser material removal patterning process, actuated by reinforcement learning-controlled XYZ stages, is demonstrated, aiming to provide automatic path-planning and a self-correction ability to the patterning process. This work builds upon previous work by the authors that showed the capability of reinforcement learning (RL) for automated movement of small particles through a maze via the laser tweezers effect [1], and for deep learning for controlling the number of pulses used for machining through a thin film [2]. Here the application of reinforcement learning for experimental control of the spatial positions of laser pulses during laser machining is presented.

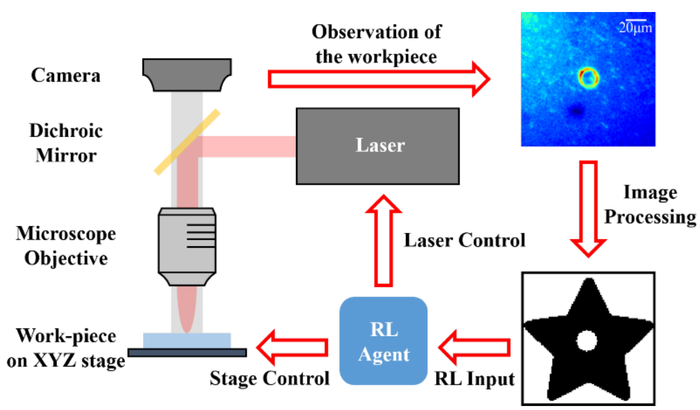

Fig. 1 Experiment apparatus.

The experimental apparatus is depicted in Fig. 1, where pulses from a *Pharos PH1-SP-1mJ* (190 fs, 1025 nm) laser system are directed via a dichroic mirror and imaged onto a 1 mm-thick glass slide using a Nikon 20x microscope objective (0.4 NA). The glass workpiece is translated by motorized XYZ linear stages, and a CMOS camera (*Thorlabs DCC1645C*) is positioned above the dichroic mirror so that real-time observations of the workpiece can be made during the laser machining process. The aim of the experiment was to laser machine a pre-defined target pattern via the following cycle of repeating steps: An image captured by the CMOS camera is segmented (with subtraction from the previous cycle camera image) to identify newly laser machined areas and hence determine the target area that still remains to be machined. This information is then compiled to an input (in the form of an image) for a decision-making RL agent. Lastly, the RL agent deduces, based on the received information, the XY position where the next pulse should be applied and requests this action from the translation stages and laser. This feedback loop was repeated until the RL agent determined that subsequent laser pulses could not further improve the fidelity of the laser-machined sample with reference to the target pattern.

RL is an area of research that mimics the basic learning process of biological entities capable of learning and decision-making (e.g., classic conditioning) [3]. Through repeated interaction with a reward-granting environment, RL agents optimise an internal behaviour policy to maximise rewards. Here, a virtual 'gym' environment that imitates the laser removal process was used for training. In this work the Proximal Policy Optimization (PPO) algorithm, incorporating Self-Imitation Learning (SIL), is adopted.

Fig. 2 shows an example experimental result of the laser machining process that is supervised by the RL agent, where the target pattern is randomly generated during the experiment. The RL agent, when trained in the gym environment, gains experience performing path-planning for a large number of randomly generated target patterns and consequently learns a generalized strategy for efficient laser machining of random patterns.

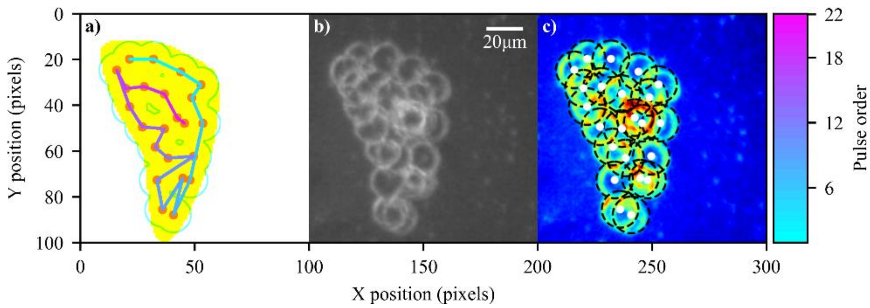

Fig. 2 a) The target pattern (yellow area) overlaid with a coloured line that connects the centres of sequential incident laser pulses. b) Camera image of the experiment result. c) Image processing (black dashed circles are the outlines of the individual incident laser pulses and white dots are the centres of the black dashed circles).

Fig. 3 demonstrates the self-correction ability of the RL agent. This ability stems from the PPO algorithm itself, which embeds stochasticity in its learning process (i.e., by optimising a Gaussian distributed policy), and hence the path-planning automatically allows for the occurrence of errors. In the physical experiment (e.g., Fig. 2), backlash in the linear stages and inaccurate registration of machined areas in image processing can introduce a lack of precision to the executed actions deduced by the RL agent; it is the intrinsic tolerance of the RL agent which ensures that the laser patterning can nevertheless still be carried out successfully.

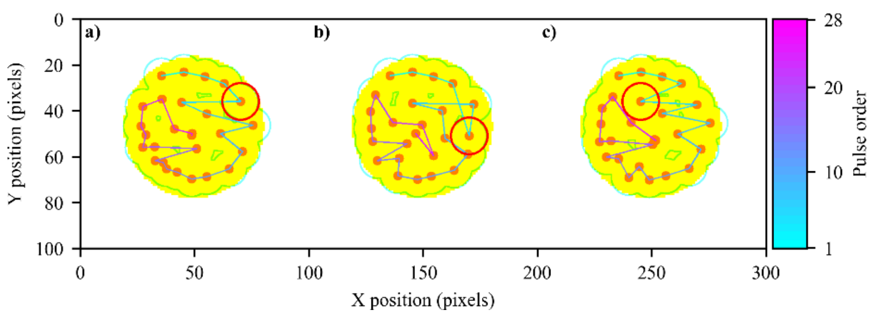

Fig. 3 Demonstration of capability of RL agent for real-time compensation of incorrectly positioned laser pulses. a) Simulation of machining a circular target pattern where the 5th pulse is highlighted in red. b) and c) Simulations of machining the same target pattern, but with the 5th pulse deliberately shifted to different adjacent positions.

In conclusion, we have developed a novel control system based on reinforcement learning, for subtractive laser patterning. The approach enabled a set of machining positions to be progressively identified for random target shapes, and also to update the chosen positions, in real time, in the event that misplaced incident laser pulses occur.

5. References

[1] M. Praeger, Y. Xie, J. A. Grant-Jacob, R. W. Eason, and B. Mills, "Playing optical tweezers with deep reinforcement learning: in virtual, physical and augmented environments," Machine Learning: Science and Technology **2**, 035024 (2021).

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[3] R. S. Sutton and A. G. Barto, Reinforcement learning: An introduction. MIT press, (2018).