Machine-learning-enhanced femtosecond-laser machining: towards an efficient and deterministic process control

Jian Gao[1], *Wenkun* Xie[1*], *Xichun* Luo[1], and *Yi* Qin[1]

[1]Centre for Precision Manufacturing, DMEM, University of Strathclyde, Glasgow, G1 1XJ, UK

Abstract. Femtosecond laser nanomachining represents a frontier in precision manufacturing, excelling in micro- and nanopatterning across diverse materials. However, its wider adoption is hindered by unintended surface damage or modifications stemming from complex non-linear laser-material interactions. Moreover, traditional effective process optimisation effort to mitigate these issues typically necessitate extensive and time-consuming trial-and-error testing. In this scenario, machine learning (ML) has emerged as a powerful solution to address these challenges. This paper provides an overview of ML's contributions to making femtosecond laser machining a more deterministic and efficient technique. Leveraging data from laser parameters and both *in-situ* and *ex-situ* imaging of processing outcomes, ML techniques—spanning supervised learning, unsupervised learning, and reinforcement learning—can significantly enhance process monitoring, process modeling and prediction, parameter optimisation, and autonomous beam path planning. These developments propel femtosecond laser towards an essential tool for micro- and nanomanufacturing, enabling precise control over machining outcomes and deepening our understanding of the laser machining process.

1 Introduction

Femtosecond laser, with pulse durations of 10^{-15} seconds, plays a pivotal role in micro- and nanomanufacturing. Through its interacting with materials, various micro- and nanostructures can be created through direct ablation or the interference of laser and laser-excited electric field. The ultra-short pulse widths and exceptionally high peak intensities of femtosecond lasers can enable high spatial resolution, minimal heat-affected zones, and non-contact processing, offering advantages over traditional techniques like nanoimprinting, ion beam processing, and electron beam lithography in terms of flexibility, speed, cost-effectiveness, and environmental impact [1]. However, femtosecond laser machining faces challenges in unintended surface damage and modifications, particularly at high intensities or due to suboptimal parameters. Consequently, surfaces machined with femtosecond lasers may exhibit lower quality and structural consistency, resulting in diminished functional

* Corresponding author: w.xie@strath.ac.uk

performance [2,3]. At its core, this issue stems from the highly nonlinear and complex interactions between the laser and material properties, leading to unpredictable outcomes. Conventional physical models often fall short in explaining these microscale non-linear phenomena, and atomistic simulations struggle to accurately represent the results due to the challenges of scaling and multiple interacting variables [4,5]. Consequently, extensive trial-and-error experimentation and significant expertise are required for effective process monitoring, control, and optimisation, which can compromise laser machining efficiency and ease of use [6].

To counter these challenges, it is imperative to incorporate advanced process control and monitoring methods, such as real-time monitoring, process modelling, path planning, and parameter optimisation. These measures foster a quick comprehension of manufacturing conditions, interpret parametric dependence, bolster predictability, and enable active and autonomous execution with minimal need for human intervention. These approaches not only addresses the limitations of traditional theoretical models and simulations, but also eliminates the dependency on trial-and-error tests, signifying a move towards a more robust femtosecond laser machining platform. Achieving this heightened control necessitates strategic process control methodologies complemented by swift feedback through *in-situ* or *ex-situ* imaging, to precisely understand and steer the manufacturing process of micro- and nanostructures. Moreover, the intricate processes involved in femtosecond laser machining, coupled with the deployment of advanced monitoring and feedback control technologies, often result in the generation of vast volumes of data. Machine learning (ML) stands out as a pivotal solution to perform data analysis and interpretation. By harnessing ML's capability to automatically learn from data, it facilitates feature extraction, classification, and data generation, thus providing an effective and efficient route to navigate these challenges. Despite its great potential, the advancements and application of ML in femtosecond laser machining have been scarcely discussed. This paper aims to bridge this gap by providing an overview of ML applications in process control and monitoring within femtosecond laser manufacturing, highlighting aspects like feature identification, *in-situ* monitoring, predictive modelling, parameter optimisation, and autonomous beam path planning. This review aims to underscore the transformative impact of ML, driving the future of high-quality and efficient femtosecond laser machining for micro- and nanostructures.

2 ML in laser machining

ML, as a subfield of artificial intelligence, is normally referred as the "Field of study that gives computers the ability to learn without being explicitly programmed" [7]. Practically, such approaches and algorithms allow the automatic learning of properties directly from data without relying on explicit theoretical descriptions based on fundamental physical mechanisms [8]. This broad field can advance laser machining in a variety of aspects, including process monitoring, parameter optimisation, process modelling, and path planning. These tasks can be achieved through three types of ML methods: supervised learning, unsupervised learning, and reinforcement learning (RL) as shown in Figure 1.

Supervised learing aims to establish the relationships between labelled input and labelled output parameters. Typically, supervised learning can be used to classify the machining results by identifying the laser-induced modifications, material types, and machining depth. A popular example is the convolutional neural networks (CNNs), which is primarily used in analysing visual imagery, characterised by their use of convolutional layers that automatically and adaptively learn spatial hierarchies of features from input images. Also, supervised learning (typically a classifier) can help to build the relationships between the input parameters and labelled results of laser manufacturing process. This method can model and predict processing results, obtain the optimised laser machining parameters, and facilitate the understanding of laser machining mechanisms. Unsupervised learning deals with unlabelled data, with the ability to identify inherent patterns and relationships in data, the characteristics of which might be partially or entirely unknown. Based on these features, unsupervised learning, especially the generative networks (GANs), offer an alternative instant process modelling method that can model the laser machined results using *in-situ* obtained images. Reinforcement learning (RL) is a different type of ML than other approaches, as it implements an agent to learn how to behave in an environment by taking actions and receiving rewards or penalties [9,10]. The goal of the agent is to maximise the cumulative reward over time. Through this method, laser machining path can be autonomously generated. In some cases, combinations of these ML algorithms are necessary to achieve a higher level of advancement of laser machining.

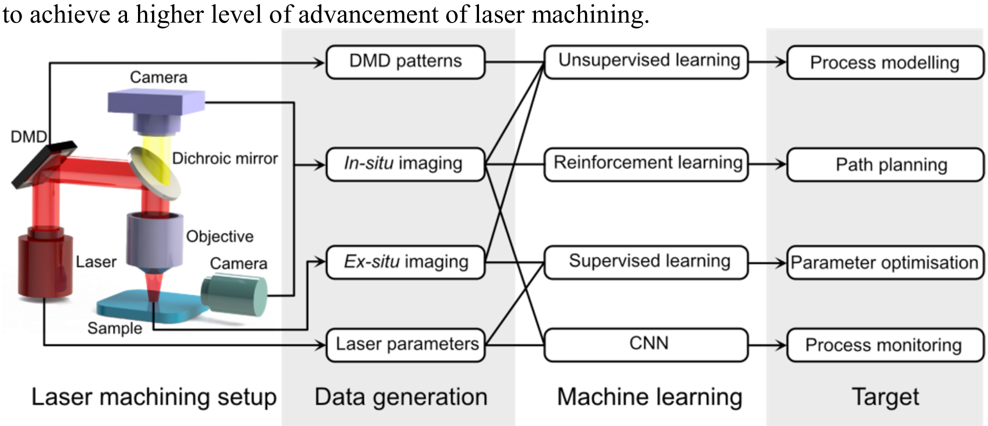

Figure 1. A schematic showing the application of ML in laser machining.

3 Femtosecond laser machining

This section will detail ML methods, in enhancing femtosecond laser machining in process monitoring, process modelling and prediction, parameter optimisation, and laser beam path planning.

3.1 Computer vision enabled process monitoring

Fast and reliably acquiring the laser machined result is critical to understand the laser machining process, further providing guidance for process control. CNNs were widely used to achieve process real-time detection and monitoring of laser machining through extracting features from images of laser machined surfaces. Xie et al. [11] applied CNNs for system monitoring via real-time visual observation of the workpiece during laser processing. Through their ML algorithms, unintended laser beam modifications were automatedly detected and quantified. They also performed the CNNs-based depth detection, further allowing the feedback-controlled laser processing at certain thicknesses. Similarly, Mills et al. [12] used CNNs in visual observation (see **Figure 2** (a)) to demonstrate the process monitoring by identifying the type of material, laser influence and the number of pulses from a single image of the sample. These parameters could be determined within ten milliseconds through a single sample image. Through both of their studies, the visual observation assisted by CNNs demonstrate great potentials in the development of automated and feedback-controlled laser machining processes through integrating pattern identification and *in-situ* process monitoring.

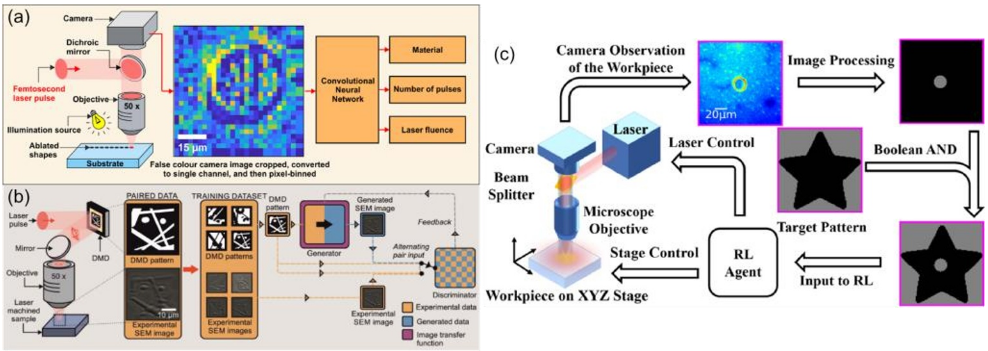

Figure 2. Schematic for using ML for laser machining. (a) CNNs for the identification of laser machining parameters. Reprinted with permission from Ref [12]. CC BY 3.0 (2019). (b) GANs for process prediction. Reprinted with permission from Ref [13]. CC BY 4.0 (2018). (c) RL for autonomous motion control. Reprinted with permission from Ref [14]. CC BY 4.0 (2022).

3.2 Parameter optimisation

Traditionally, optimizing processing parameters for laser machining has heavily relied on expert knowledge and extensive, time-consuming experiments. ML introduces efficient and intelligent alternatives for rapid parameter optimisation, addressing the significant impact of the intricate dynamics between laser processing parameters and material properties on the quality of laser-machined surfaces. Wang et al. [15] introduced a hybrid ML approach to pinpoint the optimal processing window for laser-induced periodic surface structures (LIPSS) using femtosecond laser. First, they employed an unsupervised k-means clustering to dimension reduced image data to classify laser machined nanostructures into the categories of good or bad quality. Then, they compared a range of classification ML algorithms, including hybrid ML, artificial neural networks (ANNs), random forest (RF), decision tree, support vector machine (SVM), K-Nearest Neighbors (KNNs), and the Naive Bayesian Classifier (NBC) to train the input laser parameters and SEM images for the prediction of laser machined results. The decision tree stood out for its high accuracy, achieving a 96.7% success rate in predicting laser processing outcomes. Velli et al. [16] undertook training and evaluation of ML-based probabilistic classifier on the prediction of outcome (including roughness, ripples, grooves, and spikes) based on laser's fluence and number of pulses for LIPSSs on a range of materials. The surveyed predictive models include KNNs, Gaussian Naive Bayes (GNB), Logistic Regression Model (LRM), Support Vector Classifier (SVC), and Gradient Boosting Classifier (GBC). These models effectively linked the laser input variables with the resulting material structures, and their accuracy was further enhanced when using more sampling points by integrating with simulation data. Their research demonstrated that an ML approach could streamline the calibration of laser parameters, thereby accelerating the process optimisation and enhancing its reliability over traditional trial-and-error methods.

3.3 Process modelling and prediction

Generative networks offer alternative methods to model and predict the laser machining processes. Unlike traditional methods that rely on theoretical understanding derived from first principles, neural networks can directly model the process based on data from laser machining experiment. This data-driven approach ensures the inclusion of all physical effects, even those not fully understood, within the ML algorithm. Mills et al. [13] utilised a conditional GAN (cGAN) algorithm to predict outcomes in the laser machining process with schematic showing in **Figure 2** (b). They trained the cGAN on paired datasets, which comprised laser spatial intensity profiles from digital micromirror device (DMD) alongside their corresponding SEM images of laser-machined targets. Through post-training, the algorithm established a model linking the two, enabling simulation and visualisation of laser machining results for any given laser spatial intensity profile. McDonnell et al. [17] also demonstrated the possibility of cGAN to predict multi-exposed pattern. Similarly, Heath et al. [18] used a conditional adversarial network (CAN) to achieve the prediction of the laser-machined surfaces based on the training between interferometrical 3D profiles and DMD profiles. Grant-Jacob et al. [19] applied cGAN for the prediction of laser-machined surface. Through the training among laser pulse energies, visualised surface, and images of plasma, they found the images of plasma can identify the laser pulse energy and the visualisation of sample surface. This work shows potentials for real-time visualisation of machined surface when direct observation is not possible.

3.4 Path planning

A crucial phase in laser nanomachining processes involves converting the intended design into coordinates or toolpaths compatible with the motion control hardware. This step is essential for ensuring efficient processing and achieving a high-quality finish. Despite assistance from proprietary software, toolpath design often demands significant skilled manual effort, which could be unreliable and time-consuming, hindering the mass production of laser machined products. This highlights the requirement for automated tool path planning with capabilities to perform detection and compensation for unintended actions. Xie et al. [14,20] introduced a novel laser machining approach with process controlled and supervised by RL as shown in Figure 2 (c). Through its training in a virtual environment, this approach can achieve automatic toolpath design and real-time computer vision-enabled feedback. The real-time monitoring was achieved by pinpointing where the next laser pulse should land based on real-time workpiece observations. This feedback, combined with the proximal policy optimisation algorithm's inherent resilience to action variability, equipped the RL agent to auto-correct machining discrepancies, such as those from stage vibrations. The system's robustness against such disturbances was showcased in a virtual setting by intentionally misplacing certain laser pulses.

4 Conclusions

In summary, femtosecond lasers, with their ultra-short pulses, are key to advanced micro- and nanomanufacturing, offering precision and minimal thermal impact. However, the unpredictability and complexity of their machining processes call for extensive expertise. To mitigate these challenges, integrating advanced process control and ML emerges as a pivotal advancement, enhancing efficiency, precision, and predictability in manufacturing micro- and nanostructures.

This review underscores the significant roles of ML in revolutionising femtosecond laser machining. By leveraging ML to navigate the intricate data, variables, and images obtained in laser machining, femtosecond laser machining can reach a greater determinism and efficiency through assisting process monitoring, process modelling and prediction, parameter optimisation and autonomous beam path planning. Continued exploration of machine learning's capabilities is expected to drive further advancements in micro- and nanoscale manufacturing technologies, heralding a bright future for femtosecond laser applications.

However, there are challenges hindering further application of ML in femtosecond laser machining. Key issues include the need to incorporate a broader range of structural parameters like laser polarisation and material composition, limited data availability and high testing costs, the opaque "black box" nature of deep learning models hindering user understanding and control, challenges in achieving model interpretability, and difficulties in accurately modelling and predicting three-dimensional features. Addressing these challenges is essential for advancing femtosecond laser nanomachining technology.

Acknowledgements

The authors would like to thank UKRI Fellowship programme (EP/X021963/1), Royal Society Research Grant (RGS\R1\231486), and EPSRC (EP/K018345/1, EP/T024844/1, EP/V055208/1) to provide financial support to this research.

References

1. T. c. Chong, M. h. Hong, and L. p. Shi, Laser & Photonics Reviews **4**, 123 (2010).
2. J. Gao, X. C. Luo, F. Z. Fang, and J. N. Sun, Int. J. Extrem. Manuf. **4**, 012001 (2021).
3. B. Rethfeld, D. S. Ivanov, M. E. Garcia, and S. I. Anisimov, Journal of Physics D **50**, 193001 (2017).
4. J. A. Grant-Jacob, B. Mills, and R. W. Eason, J. Phys. D: Appl. Phys. **47**, 055105 (2014).
5. Z. Lin, L. V. Zhigilei, and V. Celli, Physical Review B **77**, 075133 (2008).
6. I. H. Chowdhury and X. Xu, Numerical Heat Transfer Part A-Applications **44**, 219 (2003).
7. A. L. Samuel, IBM Journal of Research and Development **3**, 210 (1959).
8. T. Wuest, D. Weimer, C. Irgens, and K.-D. Thoben, Production & Manufacturing Research **4**, 23 (2016).
9. R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*, Second edition (The MIT Press, Cambridge, Massachusetts, 2018).
10. P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger, Proceedings of the AAAI Conference on Artificial Intelligence **32**, (2018).
11. Y. Xie, D. J. Heath, J. A. Grant-Jacob, B. S. Mackay, M. D. T. McDonnell, M. Praeger, R. W. Eason, and B. Mills, J. Phys. Photonics **1**, 035002 (2019).
12. B. Mills, D. J. Heath, J. A. Grant-Jacob, Y. Xie, and R. W. Eason, J. Phys. Photonics **1**, 015008 (2018).
13. B. Mills, D. J. Heath, J. A. Grant-Jacob, and R. W. Eason, Optics Express **26**, 17245 (2018).
14. Y. Xie, M. Praeger, J. Grant-Jacob, R. Eason, and B. Mills, Optics Express **30**, 20963 (2022).
15. B. Wang, P. Wang, J. Song, Y. C. Lam, H. Song, Y. Wang, and S. Liu, Journal of Materials Processing Technology **308**, 117716 (2022).
16. M.-C. Velli, G. D. Tsibidis, A. Mimidis, E. Skoulas, Y. Pantazis, and E. Stratakis, Journal of Applied Physics **128**, 183102 (2020).
17. M. D. T. McDonnell, J. A. Grant-Jacob, B. Mills, Y. Xie, B. S. Mackay, M. Praeger, and R. W. Eason, Optics Express **28**, 14627 (2020).
18. D. J. Heath, J. A. Grant-Jacob, Y. Xie, B. S. Mackay, J. A. G. Baker, Robert W. Eason, Benjamin Mills, and Ben Mills, Optics Express **26**, 21574 (2018).
19. J. Grant-Jacob, B. Mills, and M. Zervas, Optics Continuum **2**, 1678 (2023).
20. Y. Xie, M. Praeger, J. A. Grant-Jacob, R. W. Eason, and B. Mills, in *Conference on Lasers and Electro-Optics* (2022).