Predicting the Surface Topography of Stainless Steel Cut by Fibre Laser via Deep Learning

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Abstract: Predicting target material topography resulting from fibre laser cutting is challenging. We show that deep learning offers a data-driven capability for predicting the topography of 2mm thick laser machined stainless steel for different cutting speeds.

Fibre laser cutting is a non-contact materials processing technique that is widely used in industries. It is fast, precise and can be applied to a wide variety of materials. A limitation of fibre laser cutting is the formation of defects across the surface of the cut. There are systematic defects, such as striations, often observed as ridges across the sample, and more random defects, such as welts, observed as round depressions. Due to the non-linear nature of the underlying processes involved in fibre laser cutting, the origins of these defects are not fully understood [1], and hence predicting the topography of the laser cut sample is challenging. In recent years, there has been great interest in the application of neural networks to the field of laser machining [2-5]. Recent work by the authors showed that neural networks could predict the appearance of microscope images of defects caused by laser machining [4]. Here, we extend this capability to 3D, and use neural networks to predict a representative topography of fibre laser cutting defects under different laser scanning speeds.

Ten 2 mm thick stainless steel samples were cut with a 6 kW continuous wave fibre laser using a 100 µm multimode delivery fibre. The workstation was a TRUMPF TruLaser 1030 flatbed cutting machine with a Precitec ProCutter cutting head, with a 2.0x magnification using nitrogen as the co-axial assist gas. The focal spot size was 200 µm, positioned 2 mm below the surface. Edges were measured using interferometric profiling on a GBS SmartWLI Compact topographic profiler (Omniscan) using a Nikon 5x Michelson interferometric objective lens (CF IC EPI Plan TI) giving 1.34 µm spatial resolution, 0.57 µm depth resolution and 3.4 x 2.8 mm^2 field of view.

Fig. 1 a) illustrates the laser cutting process with an example of an experimental topography plotted in 2D and 3D. Fig. 1 b) shows the concept for the usage of a 'prediction neural network' in order to produce topographies from the cutting speed. Fig 1 c) shows examples of experimental and predicted topographies plotted in 2D and 3D, where statistical analysis confirms strong agreement between experiment and predictions.

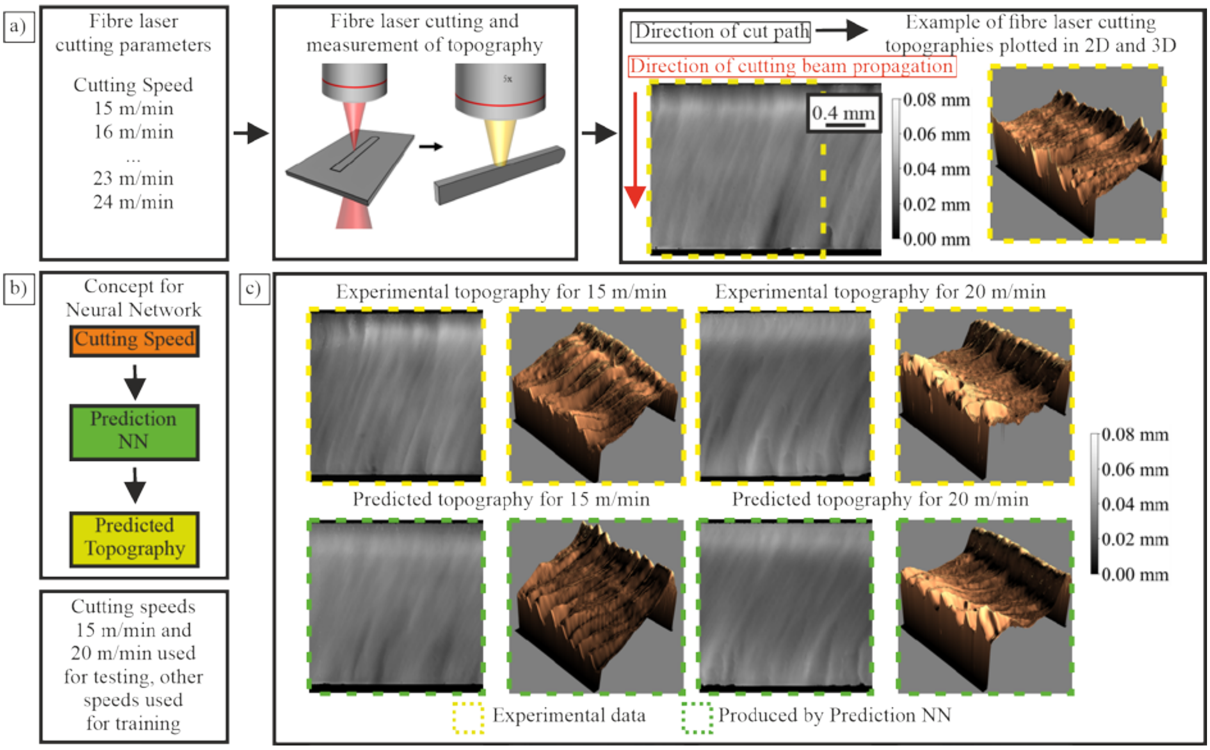

Fig. 1. Application of a neural network for predicting laser cut topography showing a) a schematic of the experimental measurement process for collecting training data, b) the concept of the neural network, and c) examples of experimental and predicted topographies.

A second neural network, referred to as the 'inpainting neural network' is presented in Fig. 2, which shows that it can be used to predict a larger field of view of topography, using 20 m/min as an example. This is made possible via a chaining process where each predicted image can be split in two, separated, and then the central region filled in via the inpainting network. Critically, the two networks can be used in combination, where the 'prediction neural network' makes a topography prediction, and the 'inpainting neural network' can be used recursively on the predicted topographical image to produce a larger field of view as shown in Fig. 2 c).

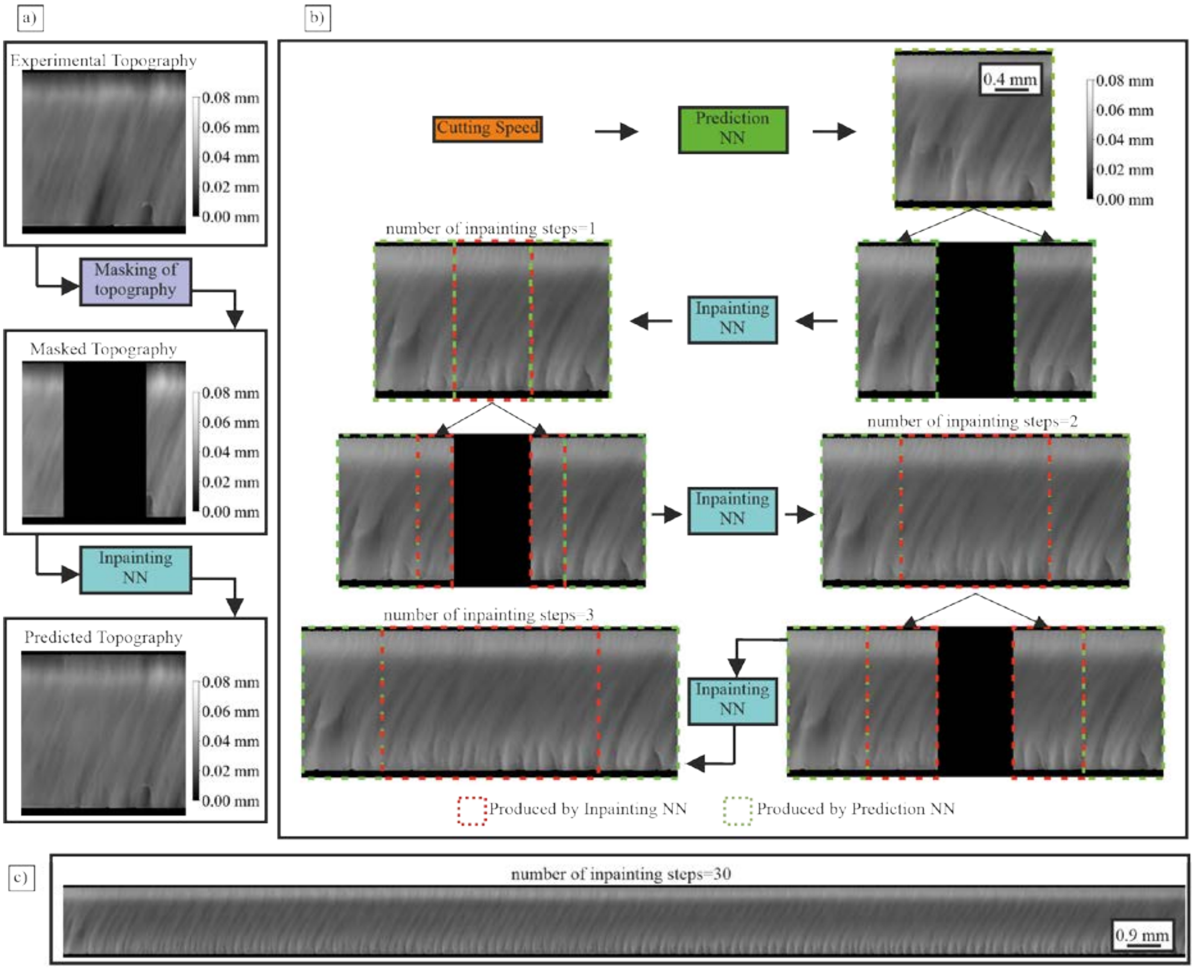

Fig. 2. a) Diagram showing the neural network process for inpainting. b) Flowchart showing how inpainting can be used to predict large sections of topographic data. c) Example of a large section of laser cutting topography predicted via the two neural networks in combination.

In conclusion, a two-step neural network based approach was used to predict the topography of laser cut 2 mm thick stainless steel. The first step was to predict the fibre laser cutting topography directly from fibre laser cutting input parameters, as shown in Fig. 1. The second step was to fill in a gap of topographical information based on the topography surrounding the gap using an inpainting neural network, as shown in Fig 2. This approach of combining both neural networks to visualise large sections of fibre laser cutting topography in 3D could also be applied to other laser cutting parameters, such as assist gas pressure, focal focus position and stand-off distance. The combination of parameters could then be optimised in order to minimise the occurrence of defects, and help to quantify the statistical nature of defect production.

References:

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