Studying the Topography of Laser Cut Aluminium Using Latent Space Produced by Deep Learning

Alexander F. Courtier[1], Matthew Praeger[1], James A. Grant-Jacob[1], Christophe Codemard[2], Paul Harrison[2], Ben Mills[1] and Michalis N. Zervas[1]

[1]Optoelectronics Research Centre, University of Southampton, University Road, Southampton, SO17 1BJ, U.K.

[2]TRUMPF Lasers UK, 6 Wellington Park, Toolbar Way, Hedge End, Southampton, SO30 2QU, U.K.

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Abstract: Modelling topography resulting from laser cutting is challenging due to the highly non-linear light-matter interactions that occur during cutting. We show that unsupervised deep learning offers a data-driven capability for modelling the changes in the topography of 3mm thick, laser cut, aluminium, under different cutting conditions. This was achieved by analysing the parameter space encoded by the neural network, to interpolate between output topographies for different laser cutting parameter settings. This method enabled the use of neural network parameters to determine relationships between input laser cutting parameters, such as cutting speed or focus position, and output laser cutting parameters, such as verticality or dross formation. These relationships can then be used to optimise the laser cutting process.

1 INTRODUCTION

Fibre laser cutting is a materials processing technique with many applications in industry. It offers many advantages over competing techniques in terms of precision, speed, and mechanical stability. Defects can however be formed during cutting that limit the final quality of the cut. These defects include striations, seen as systematic ridges along the cutting edge, as well as welts, seen as random depressions along the sample.

The interactions causing these defects are poorly understood due to their non-linearity (Arai, 2014), so determining their relationship to input parameters is challenging. Deep learning enables a data driven approach to studying laser machining processes, with much interest shown in recent years (Courtier et al, 2021; McDonnel et al, 2021; Stadter et al, 2020; Mills and Grant-Jacob, 2021). Unsupervised learning enables the use of unlabelled laser cut topographies from which neural networks can extract their own mathematical models. This enables the use of a latent parameter space to model the relationships between laser cutting input parameters, such as the cutting speed or the focus position, and laser cutting output parameters, such as verticality or dross formation.

2 EXPERIMENTAL METHODS

Sixty-five 3 mm thick grade 1000 aluminium samples were cut with a 4 kW continuous wave disk laser. The workstation was a TRUMPF TruLaser 1030 flatbed cutting machine with a Precitec ProCutter cutting head, with a 2.0x magnification focusing objective and using nitrogen as the co-axial assist gas. The focal spot size was 210 µm. Edges were measured using interferometric profiling on a SmartWLI Compact topographic profiler (GBS) 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 field of view.

The focus position is defined as the distance between the focus of the laser and the sample surface, and the standoff distance is defined as the separation between the laser cutting head and the work piece. Each of these parameters have a dependence on each other, for example standoff distance will impact the effect of gas pressure.

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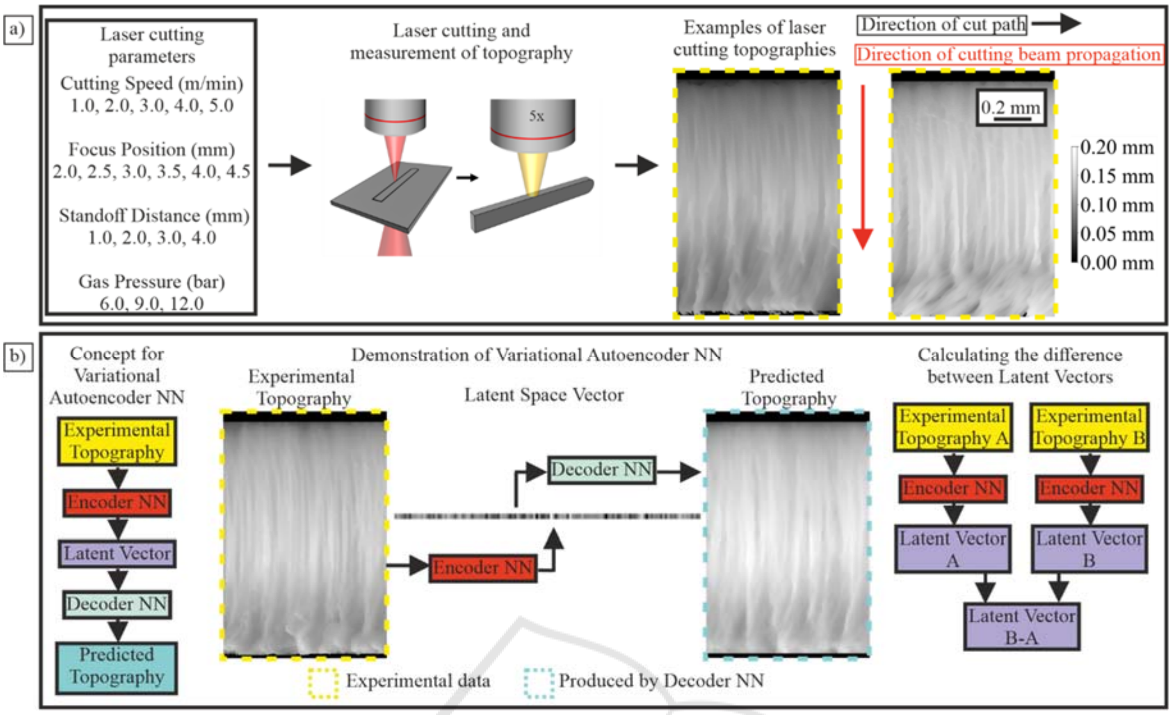

Figure 1: Application of a neural network for measuring the latent space of laser cut topography showing a) a schematic of the experimental measurement process for collecting training data, and b) the concept of the prediction neural network with a demonstration using topographic data, which also shows a concept of calculating the difference between latent vectors for different parameters.

3 RESULTS AND DISCUSSION

Fig. 1 a) illustrates the laser cutting process with an example of an experimental topography. Fig 1 b) shows the concept of a Convolutional Variational Autoencoder (CVAE) both conceptually and using topographies. I.e. The encoder neural network (NN) learns to compress the information contained within the topographic data into alower number of dimensions, more compact, representation (the latent space vector). The decoder NN learns to perform the reverse operation, rebuilding the original topographic data as accurately as possible from the latent space vector. The figure also shows a method for calculating the difference between two latent vectors which can be used to identify the effects of and interpolate between different laser cutting parameters.

Our key result is shown in Fig. 2 which demonstrates that latent vector arithmetic can be used to predict laser machining topographies. When an experimental topography is fed into our encoder network, the output is a 1D vector whose parameters represent the latent space governing the appearance of the topography. By averaging the latent vectors of many topographies that were laser machined under the same conditions, we can produce a latent vector that is representative of defects that occur under those conditions. Vector arithmetic can then be used to combine these representative latent vectors in order to predict topographies that would result from intermediate conditions. As the latent vector parameters are correlated to the input topography, the latent space can be mapped to determine the linearity of the relationship between laser cutting parameters and laser cutting defects. By comparing vector properties such as the equivalent angle between latent vectors (in multi-dimensional space) or the difference in resultant magnitude of latent vectors, it is expected that relationships between laser cutting input and output parameters can be determined. Results of this analysis will be discussed in more detail at the conference.

4 CONCLUSIONS

In conclusion, a CVAE was trained using unsupervised learning to model the appearance of laser cut grade 1000 aluminium. The resultant latent vectors were then used to model the changes in

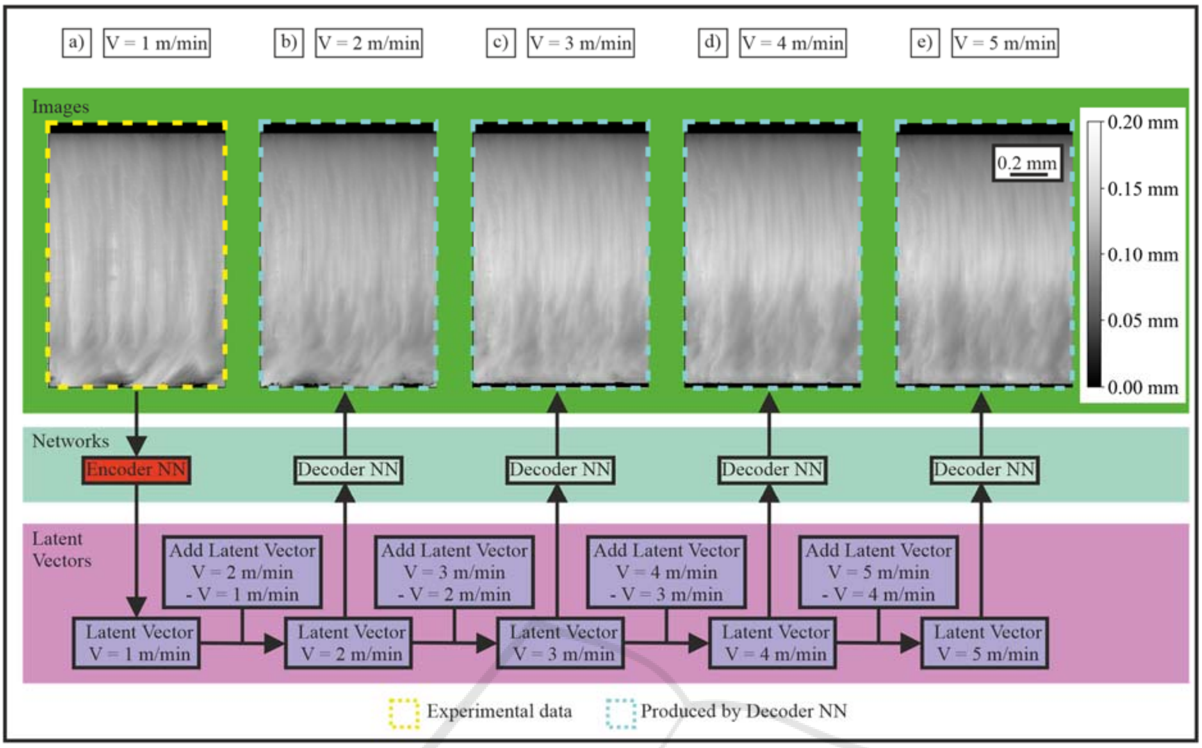

Figure 2: Diagram showing the use of latent vector arithmetic to model the changes of defects from cutting speeds of 1 m/min to 5 m/min. In these simulated topographies (i.e. produced by the Decoder NN), the focus position was 2.0 mm, the standoff distance was 4.0 mm and the gas pressure was 9 bar.

appearance using the average difference between vectors for different cutting conditions. The novelty in this approach is the use of unsupervised learning to model the relationships between laser cutting input parameters, such as the cutting speed or the focus position, and laser cutting output parameters, such as verticality or dross formation. These relationships could then be used to optimise the laser cutting process by predicting output topographies for given cutting parameters and for predicting parameter limits such as maximum or minimum cutting speeds.

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