

Ultrasonic characterisation of grain orientations, elastic tensor and geometry of thick-section welds using deep learning

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1 Abstract

Ultrasonic inspection of thick-section austenitic welds is hindered by the effects of microstructural heterogeneity: columnar grains with spatially varying crystallographic orientation distort, split and attenuate the beam, making conventional imaging based on the straight-ray assumption unreliable. This work proposes a model-based deep neural network (DNN) inversion workflow to infer weld microstructure description from time-of-flight (ToF) maps. Work to date focused on grain orientations; in this contribution, we extend it to weld geometry, array position, and the elastic tensor. Our analysis shows the importance of respective parameters for ToF prediction and the impact of their uncertainty on the inversion. Training data are generated synthetically using a fast shortest-ray-path (SRP) ray-tracing forward model. Two inverse tasks are addressed with network-based metamodels: (i) ToF-to-weld-map regression (fully-connected architecture) to estimate the orientation map ; and (ii) ToF-to-parameter regression (combined convolutional and fully-connected network). We compare the architectures and assess their generalisation using k-fold cross-validation. Grain-scale finite-element simulations and experimental FMC data from industry-relevant welds validate inversion results and demonstrate that the predicted weld maps/parameters enable improved Total Focusing Method reconstructions.

Keywords: inversion, ultrasonic tomography, austenitic welds, array imaging

2 Introduction

Material information is critically important for imaging of heterogeneous anisotropic materials. Common sources of such information are classical destructive evaluation methods, such as metallography or EBSD, and modelling, either phenomenological [1], or numerical [2, 3]. Recent years have seen an increased interest in developing non-destructive characterisation techniques based on signals recorded with ultrasonic arrays. Past work includes evolutionary algorithms [4], Bayesian approaches [5], deep learning [6] and ray-inversion [7], all focused on macroscopic grain orientations (homogenised descriptions) while keeping other parameters fixed.

Our approach relaxes this constraint, exploring the suitability of two network architectures for multi-parameter inversion.

3 Materials, Methods and Conclusions

We developed and evaluated several network architectures, one of which is shown in Fig. 1. The training dataset was generated using a fast shortest-ray-path model, with parameter spaces spanning respective ranges typical for industrial welds.

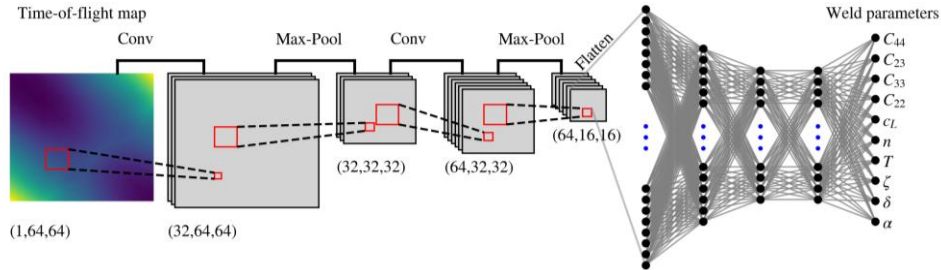


Fig. 1. Convolutional neural network layout with fully connected regression block for obtaining weld parameters.

Two mock-ups served as use cases for this study, a V-weld, and a VV-V weld (Fig. 2).

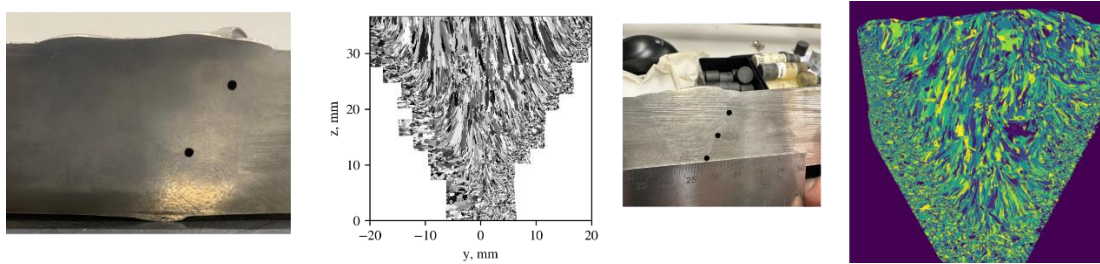


Fig. 2. Two mock-ups used in this study, and their respective EBSD scans.

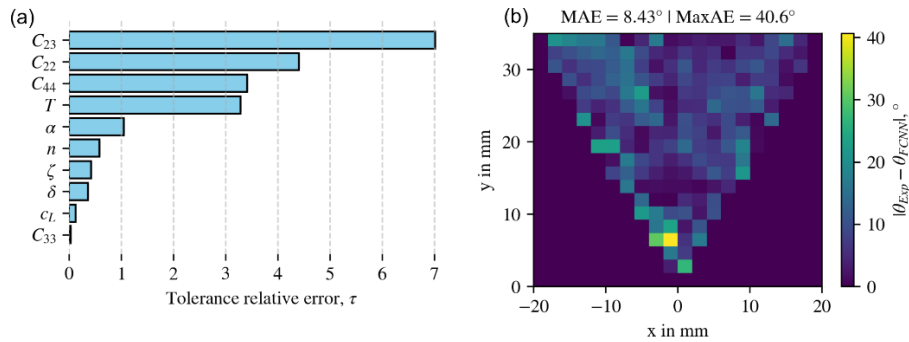


Fig. 3. Results: (a) tolerance-relative error for the FE study; (b) MAE map for the experimental case.

Our results show that the DNN inversion framework can infer both geometrical and material features. Including geometry and the elastic tensor makes the task more challenging, as some parameters are weakly sensitive. However, the architecture combining a CNN with an FCNN regression block demonstrated good performance.

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