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Quantitative characterization of ductility for fractographic analysis

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Abstract

We develop a machine-learning image segmentation pipeline that detects ductile (as opposed to brittle) fracture in fractography images. To demonstrate the validity of our approach, use is made of a set of fractography images representing fracture surfaces from cold-spray deposits. The coatings have been subjected to varying heat treatments in an effort to improve their mechanical properties. These treatments yield markedly different microstructures and result in a wide range of mechanical properties that combine brittle and ductile fracture once the materials undergo rupture. To detect regions of ductile fracture, we propose a simple machine learning network based on a 32-layers U-Net framework and trained on a set of small image patches. These regions most often contain small dimples and differ by the surface roughness. Overall, the machine-learning method shows good predictive capabilities when compared to segmentation by a human expert. Finally, we highlight other possible applications and improvements of the proposed method.

1 Introduction

Our ability to quantify the mechanical properties and inner microstructures of materials is based on mechanical testing and models, and commonly requires imaging techniques and analysis [1, 2]. To account for the complex load redistribution of stress within a material, up to crack or pore nucleation, statistical and microstructural aspects are essential [3]. In turn, to perform damage-design, versatile and robust image analysis methods must be developed to quantify and characterize microstructures [4, 5]. The present work is motivated by our need to assess and understand the mechanical response, up to rupture, of certain coatings obtained by cold-spray techniques. Cold-spray deposits generally do not present, in their initial state, satisfying mechanical properties in that respect. Nevertheless, recently-developed techniques that involve heat-treatments allow for microstructural softening [6]. Although these methods have shown promising results, optimizing on the parameters of the thermal treatments requires some level of automatization, as well as sophisticated image analysis to separate (“segment”) brittle from ductile fracture regions. A related problem, that of image classification based on failure modes, has been addressed in [7] and [8], using both classical convolutional layers for texture analysis and a modified method based on the adaptive wavelet transform. The present study addresses the problem of image segmentation rather than classification. We make use of a set of fractography images of cold-spray coatings studied in [6] that show both brittle and ductile modes of failure, thus providing an ideal application to the segmentation problem. This short article is divided in three main sections. The material and fractography images are described in Sec. (2). Secs. (3) and (4) address the deep-learning architecture and training, and our results. We conclude in Sec. (5).

2 Cold-spray deposits and fracture surface images

This work is based on cold-spray projections of 316L-stainless steel from the company “Impact Innovation”. Three thermal treatments in a MF7 furnace under air environment, at 600, 800 and 1000°C are performed, resulting in different coatings. Fracture surfaces for each sample subjected

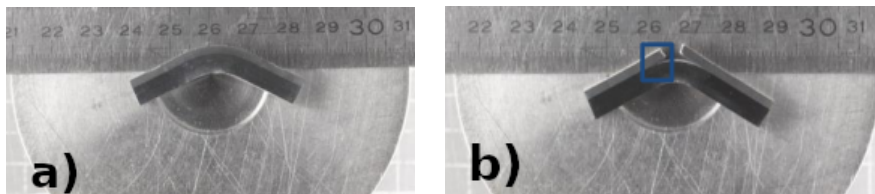


Figure 1: Three-points bending tests with (a) and without (b) heat treatment. Heat treatment significantly enhances ductility.

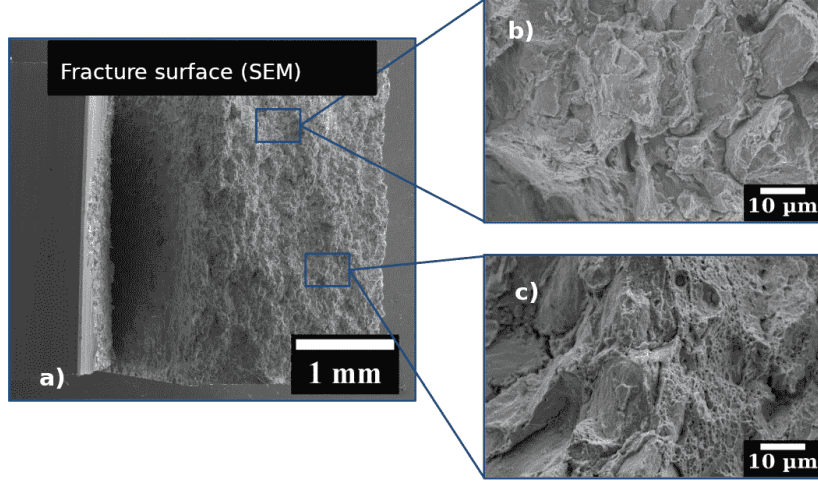


Figure 2: a) Fractography image showing regions with predominantly brittle (b) and ductile (c) rupture modes. The bottom zone in (c) undergoes maximum bending compared to (b).

to a three-points bending test (Fig. 1) are observed by scanning electron microscopy (SEM) using a Supra 55 with 15kV tension, at a 12mm working distance, a diaphragm of 240 μ m and a magnification of $\times 1500$. Secondary electron imaging, sensitive to the surface topography, has been used.

The heat treatment strongly influences the ductile response. Adhesion mechanisms, and particle-particle interfaces, are modified by the heat treatment, leading to a mixed brittle-ductile response [9]. Rupture zones, in particular, are located in particle-particle interfaces in the as-sprayed state and are not seen on the whole fracture surface [6]. As shown in the fractographic analysis in (Fig. 2), fracture surfaces display varying contrasts as a consequence of the topography, and ductile regions are constrained along surfaces that rarely exceed 10 μ m in size. A signature of these regions is the presence of dimples that are less than 1 μ m in diameter. These regions are difficult to detect automatically, yet their texture is characteristic of ductile behavior. In the following, a convolutional neural network is developed to segment ductile regions as a way to provide a more robust method than that of conventional image analysis methods. The proportion of ductile regions in fracture surfaces provides a quantitative indicator of the mechanical response of these coatings, and could be used to correlate microstructure, heat treatment as well as mechanical properties.

3 Machine learning method

In order to establish a reference dataset, we first selected 30 images per sample, each containing 1024 \times 704 pixels and showing different (disjoint)

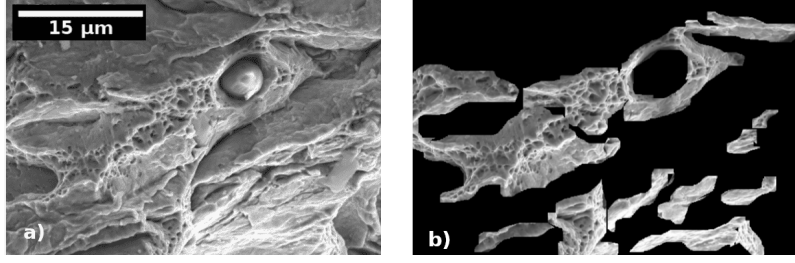


Figure 3: Annotated fractography images. a) SEM image. b) Selected ductile zones.

regions of the fracture surface, with varying contrast and brightness, as specified above. The regions undergoing ductile rupture have been manually annotated by an expert, in all images, making use of a hand-made macro incorporated in the software “ImageJ”. These regions are selected by assuming that ductile regions contain dimples and higher roughness. Each of the obtained images are binarized and cropped into 88 patches containing 128×64 pixels. Initial images have been subsequently cropped so as to be used during training. Cropping proved necessary to generate a sufficiently large number of images, while reducing the memory required for training. See Fig. (3) for an illustration of the resulting segmentation.

We have selected “U-Net” [10] architecture network for the detection and segmentation of regions with ductile fracture. This architecture, based on a series of filters organized as a “U”, allow us to perform four most important tasks: (i) convolution so as to apply one or more filters on the images; (ii) nonlinear transformation of images with the rectified linear unit (“ReLU”), so that negative values can be thresholded to zero; (iii) pooling so that the image size can be reduced while keeping track of the most important information, including maximum, mean, sum; (iv) classification with a fully-connected layer, which links each neuron on the previous layer with a neuron on the following layer, thus allowing one to classify the input pixels according to characteristics highlighted in the previous tasks. In the present study, the number of filters on the first layer is set to 32. During training both training and validation scores are measured. The first one is obtained by measuring the difference between the prediction of the network, made up of regions of ductile failure, and that manually selected by the expert whereas the validation score only takes into account those images that are not part of the training database.

The score is given by the Jaccard distance $J = 1 - |A \cap B| / |A \cup B|$ between two sets A and B , where $|\cdot|$ denotes the set surface. Fig. (4) represents the evolution of both scores during training. The scores are plotted with respect to epoch numbers. In one epoch, the algorithm uses each patch in the database once. To prevent overfitting, the algorithm is stopped when the score corresponding to the validation dataset ceases to decrease. This is determined by an additional “patience” parameter, set to 100, which prescribes the number of epochs without improvement on

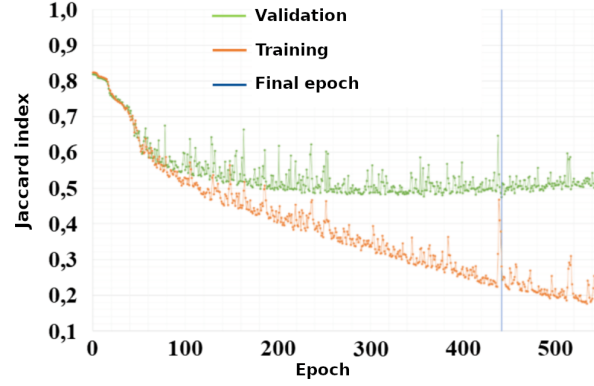


Figure 4: Validation and training Jaccard indices as a function of the number of epochs during training.

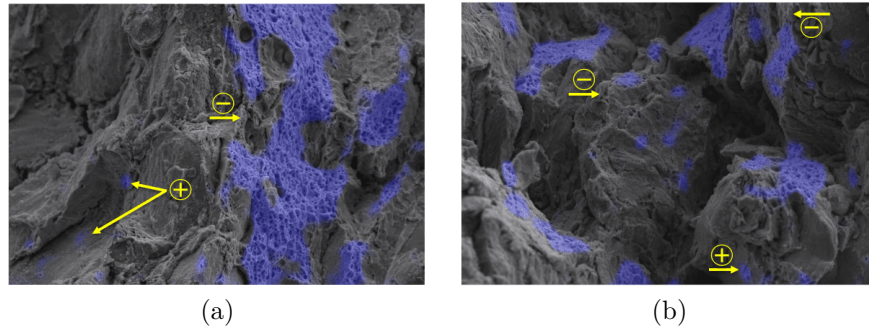


Figure 5: Two images representing the network predictions for regions undergoing ductile fracture (in blue). Over and under-detections are marked by symbols \oplus , \ominus , respectively (see text).

the validation dataset that is tolerated during training. The algorithm stopped at epoch 542, whereas the network retained is that corresponding to epoch 442.

4 Results

Two images representative of the network predictions are shown in Fig. (5) as indicated in blue. These images have been obtained by applying the trained U-net network to a set of novel fractography images. We have highlighted in both images zones where the predictions of the network are incorrect: “over-detections” (marked by the symbol \oplus), corresponding to brittle regions predicted to be ductile, and “under-detection” (symbol \ominus) for ductile zones indicated as brittle.

An error criterion is now definee in order to interpret these results.

Output images are thresholded to a value of 200 (out of a maximum of 255), and we compute in each image: (i) the number f of non-detected pixels (“false negative”); (ii) the number f' of wrongly-detected pixels (“false positive”); (iii) the number t of correct pixels (“true positive”). These statistics allow us to define the precision $p = t/(t+f')$, the recall $r = t/(t+f)$, and score $F = 2pr/(p+r)$, equal to the harmonic mean of p and r . It approaches 1 for predictions close to that of the human expert. The mean of F is about 0.46. This value corresponds to visually satisfactory segmentation results. Indeed, the F-score is strongly influenced by the exact shape of the ductile zones, which are, in effect, not precisely defined by the expert. Furthermore, we emphasize that the tool is designed to perform comparison between microstructures; accordingly, we aim to rank fractography images by ductile region surfaces, not necessarily to exactly predict the location of each ductile zone.

5 Conclusions and perspectives

In this work, use has been made of a simple U-Net architecture to segment different fracture mechanisms present in fracture surface images. The images represent complex mixed rupture modes. Ductile rupture is detected by the presence of small dimples seen in the SEM images at various angles from the plane of the image. The network devised in this study shows promising results. However, the machine-learning pipeline tends to detect fewer ductile regions than the human expert, which is conservative but penalizing. Further work is needed to enhance these results, left as outlook: (i) one may improve the image database used for training, and in particular increase the number of images, use larger image patches, or perform data augmentation based on axial symmetries, gaussian noise and rotations; (ii) modify the network architecture, such as the number of filters in the first layer; (iii) finally, one may want to adjust or pre-process input images, removing noise and using contrast-enhancing filters. Finally, we emphasize that the simple segmentation method developed in this work can be used in a variety of applications, in particular that of mixed rupture modes, as occurs in the ductile-to-brittle transition of ferritic and bainitic steels [11].

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