Quantitative fractography of void coalescence fractures

Most overload failures of structural alloys take place by a process of microvoid coalescence. The microvoids nucleate at regions of localized strain discontinuity, such as second phase particles and grain boundaries. They grow when the strain in the material increases and coalesce into a continuous fracture surface that has the appearance of dimple rupture. The size of the dimples is governed by the number and distribution of microvoids that were nucleated: when the nucleation sites are few the microvoids grow to a large size before coalescing and vice versa. The dimples can vary from a very deep form to quite a shallow one, depending on the ductility of the material and its microstructure. The dimple shape is affected by the local state of stress in the material, they are symmetric under pure tension and become elongated to different degrees under shear modes of loading. Therefore, a quantitative evaluation of the distribution of dimple size, shape and depth may be a valuable tool to estimate the state of stress and the mechanical properties of the material. By a quantitative fractography tool this estimation may be done locally, on very small pieces of material, in particular, those available during the analysis of failures.

We report our effort to develop such a tool for the analysis of dimple rupture fracture surfaces. It was done by combining image analysis with deep learning tools. We developed a **FracSegment** - an application that allows to segment and perform quantitative analysis of local distributions of size, shape, and shape ratio of the dimples (see Figure 1).

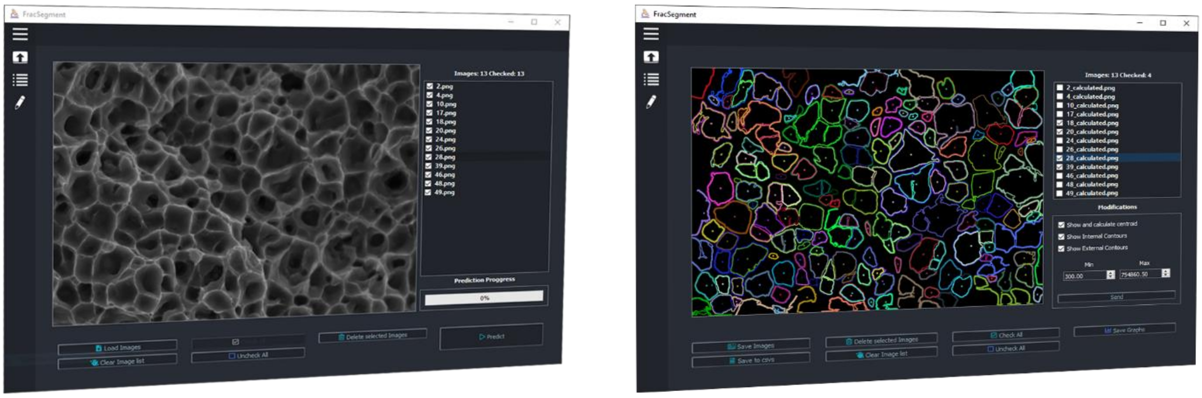

Figure 1. **FracSegment tool**: the segmented dimples are shown in the main window.

For dimples segmentation, we adopted the U-Net deep learning model [1], which initially was developed for biomedical image segmentation. We modified the input sizes of the convolutional layers and added two additional convolutional layers. To reduce the memory requirements, the model was trained on image patches of size 256×256 pixels, sampled at stride 128 pixels in the vertical and horizontal directions. For the segmentation of a new image, it is split into non-overlapping patches of size 256×256, each one is segmented and the results of all the patches are stitched together to obtain the final segmentation. The segmented dimples are analyzed using image processing techniques.

The local distribution of size, shape, and shape ratio of the dimples is correlated with the local mode of loading. An estimate of the depth and size distribution of the dimples serves to estimate the ductility of the material. This estimate is based on a quantitative correlation between the characteristics of the dimples and the ductility of the material. The ductility is the material property that determines its fracture toughness.

The application and its source code can be downloaded from GitHub
https://github.com/Mohamab29/FracSegment.

References:

1. O. Ronneberger, P. Fischer, and T. Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.