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Advances in the Automated Segmentation of 3-D Microstructures

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The reconstruction of 3-D microstructures of advanced engineering materials generally requires a series of processing steps: data acquisition (either serial section images or tomographic projections); registration of consecutive slices or projections (to ensure that they all have a common coordinate origin); intensity equalization (to ensure that all images share the same intensity scale); data clean-up (an optional step; may include noise and/or artifact removal); and, finally, data segmentation. Segmentation refers to the act of separating the 3-D data into disjoint regions, based on some criterion. In materials science, those regions likely correspond to different phases, or to differently oriented grains in a single phase, but they could also be separate tows in a 3-D woven composite material, for instance. In biological samples, the regions are often identified with individual cells or cell components.

In this contribution, we will review recent progress on three different segmentation algorithms:

- *Euclidean distance map combined with watershed transformation*: The Euclidean distance map of a binary 3-D array represents, for each voxel, the distance to the closest boundary voxel. For a polycrystalline microstructure, for instance, the distance map would show a maximum near the center of each grain. The watershed transform can be thought of as a procedure for filling 3-D valleys from the bottom up, until the "ridge(s)" surrounding the valley are reached. If the negative of the distance map is used as the array of valleys and ridges, then the watershed transform results in a segmentation of the original microstructure. We will show examples of this procedure for a Ni-based superalloy, for which, in addition to the segmentation data, lower resolution data from Orientation Imaging Microscopy was used to seed the watershed transform (Fig.1). Additional examples will include a 3-D triaxial weave, in which the individual tows can be separated using this segmentation approach.

- *Expectation Maximization with Maximization of Posterior Marginals (EMMPM) combined with Simulated Annealing*: In this approach [1], one employs a Bayesian algorithm which attempts to minimize the number of incorrectly classified voxels in a 3-D data set. The procedure assumes that the voxels belonging to a particular region have intensities with a Gaussian distribution, and attempts to determine stochastically which voxels in the data set belong to this particular Gaussian; this procedure can deal with overlapping Gaussians. We will provide examples of this approach for both Ni-based superalloys and titanium α-β two-phase microstructures (Fig.2).

- *Potts Model-based Monte Carlo Segmentation*: The ferromagnetic Potts model is a generalization of the standard Ising model, in which each spin can take on one of a range of possible states. The phase space of the Potts model consists of ferromagnetic, super-paramagnetic, and paramagnetic phases; the super-paramagnetic phase consists of domain with aligned spins. By a careful mapping of an experimental image onto the super-paramagnetic domains of a multi-state Potts model, one can segment the original image by means of a standard Monte-Carlo simulation [2]. We will present preliminary results of the application of this approach to multi-phase microstructure data sets.

References
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[2] H. Agrawal and E. Domany, *PRL*, **90** 158102 (2003).
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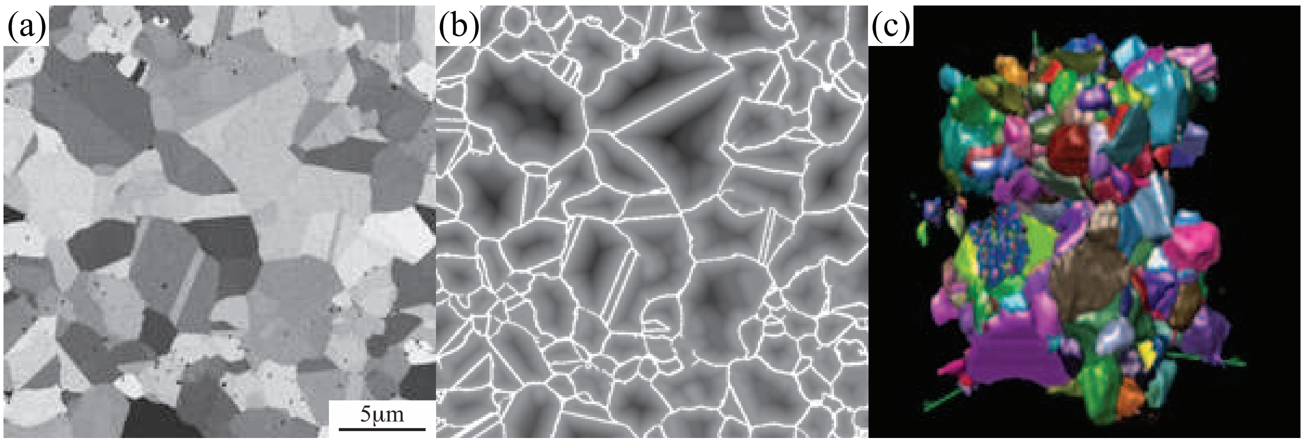

Figure 1: (a) SEM image of the grain structure of a single slice of an IN100 superalloy; (b) grayscale Euclidean distance map (darkness indicates distance to nearest grain boundary) along with a superimposed grain boundary skeleton. By employing the watershed method to fill each valley (in 3-D), all grains can be identified and displayed as a rendered microstructure (c).

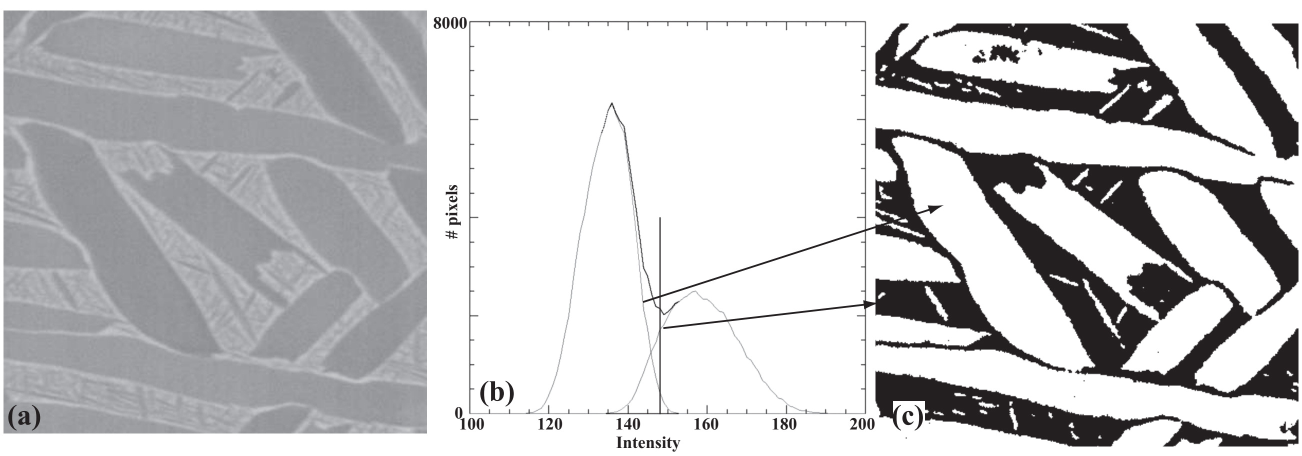

Figure 2: (a) SEM microstructure image of a two-phase Ti α-β alloy. The intensity histogram (b) shows two overlapping peaks; standard thresholding at the vertical line does not result in a good separation of the two phases. (c) shows the result of the application of the EM/MPM method using four initial segmentation classes. The two individual Gaussians in (b) show that the EM/MPM method is successful at separating pixels belonging to different phases, by minimizing the probability that a pixel is classified incorrectly. The algorithm considers the nearest neighbors of each pixel, and can also be applied in 3-D.