1966
doi:10.1017/S1431927616010679

Microsc. Microanal. 22 (Suppl 3), 2016

Stereological Techniques for Quantitative Characterization of Microstructures

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It is well known that material chemistry and processing dictate material microstructure and microstructure influences properties and performance of materials. Consequently, quantitative characterization and statistical representation of microstructure are of considerable importance in materials science. Microstructure is essentially a collection of three-dimensional volumes (for example, grains, precipitates, inclusions, pores, etc.), two-dimensional interfaces and grain boundaries, one-dimensional lines (for example, grain edges), and zero-dimensional points (for example, quadruple points in grain structure) dispersed in a three-dimensional reference space (a specimen or a component). Consequently, a microstructure can be quantitatively characterized via unbiased estimation of important geometric attributes such microstructural features. It is important to emphasize that material microstructures are three-dimensional (3D) and, therefore, the attributes of *three-dimensional* microstructural geometry are of fundamental interest. Although techniques such as computed tomography are available for direct observation of 3D microstructures [1], it is often convenient and efficient to observe and characterize microstructure in two-dimensional (2D) metallographic sections through 3D microstructure. Nonetheless, geometric attributes of 3D microstructures are of interest. Consequently, techniques for assumption-free, unbiased, and efficient estimation of attributes of 3D microstructures from the observations/measurements performed on 2D metallographic sections are of interest. Stereology (a branch of stochastic geometry) provides mathematical basis for such estimation techniques. The objective of this contribution is to review important stereological techniques and their applications for unbiased quantitative characterization and representation of 3D opaque material microstructures via interrogation of 3D microstructure using lower dimensional probes such as planes (or surfaces), lines (straight or curved), and points, or projected images [2-4]. Interestingly, these techniques can be also applied for quantitative characterization of the microstructure (pores, inclusions, facets, dimples, etc.) present in the non-planar tortuous material fracture surfaces [5-7].

According to an important theorem of stochastic geometry [8], in a 3D microstructure, a test probe of dimension k (≤ 3) can yield an unbiased estimate of a d-dimensional microstructural characteristic, when $k \geq [3 - d]$. Consequently, interrogation of 3D microstructure using geometric probes such as points, lines, and planes yields assumption-free and unbiased estimation of the geometric attributes of 3D microstructures such as volume fraction of constituent phases, total interfacial area per unit volume of each type of interface/grain boundaries, integral mean curvature of interfaces, and total length of 1D lineal features per unit volume. Sampling procedures are available for efficient estimation of these attributes in anisotropic and partially anisotropic microstructures from measurements performed on sectioning planes/projections of at the most three different orientations [9-11]. Stereological techniques are widely used for characterization of biological structures. Applications of these efficient techniques to material microstructures will be demonstrated in this presentation. Parameters such as average grain size, mean free path, and average interfacial curvature can be calculated from such data in a straight forward manner. Consequently, for applications in materials science and engineering where microstructure characterization is limited to estimation of metric properties like volume fraction, total interfacial are per unit volume, total length per unit volume, and integral mean curvature, there is no need to reconstruct and visualize three-dimensional microstructure.

In some microstructure characterization applications, it is of interest to estimate number density of features (precipitates, grains, inclusions, voids, etc.) present in 3D microstructure. Unfortunately, in general, number density in 3D microstructure cannot be estimated from any measurements performed on two-dimensional metallographic sections. Nonetheless, reconstruction and visualization of 3D microstructure is not required for unbiased estimation of number density. Sterio [12] has shown that number density can be estimated using disector probe that consists of two parallel closely spaced metallographic sections if the observations can be performed on both planes to determine the number of features present in one plane that are absent in the other plane. Efficient estimation of number density in opaque 3D material microstructures is possible using a combination of digital image processing and disector probe [13].

During the past decade or so, efficient stereological techniques have been developed for detailed statistical/mathematical representation of material microstructures using orientation dependent n-point correlation functions [14] and lineal path probability distributions [15] of 3D microstructures which can be estimated from the measurements performed on two-dimensional metallographic sections. Such microstructure representations are useful for computer simulations of realistic microstructures [16, 17]. These recent developments will be presented.

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