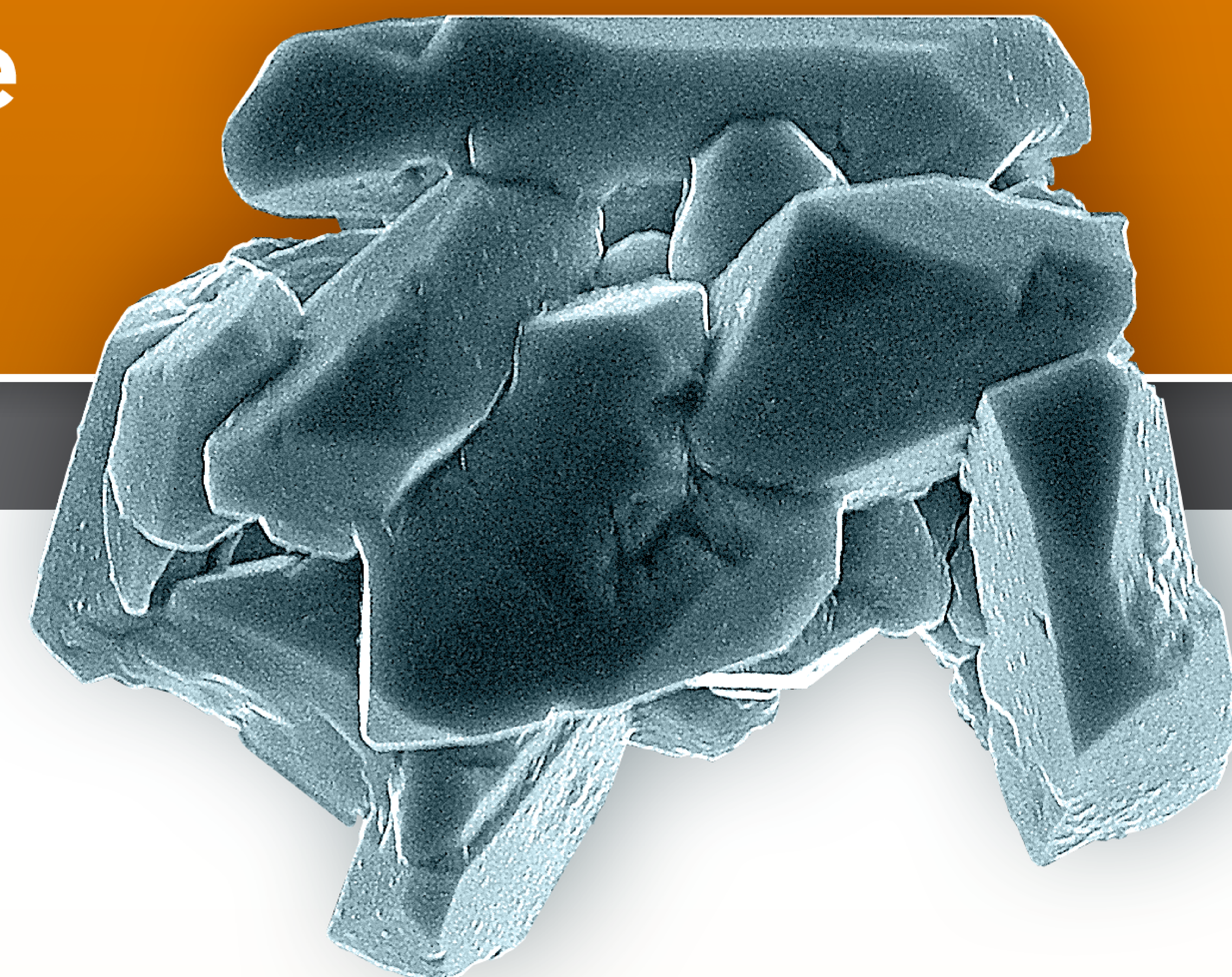
Automated Classification of Scanning Electron Microscope Particle Images using Morphological Analysis



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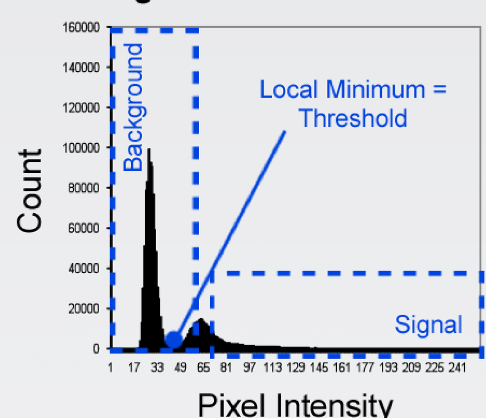
Introduction

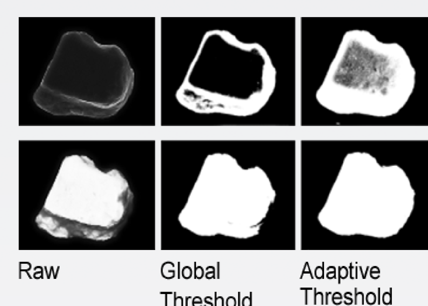
We are developing a software tool that can automatically classify anthropogenic and natural aerosol particulates using morphological analysis. Our method was developed using background and secondary scanning electron microscope (SEM) images of single particles. Particle silhouettes are detected and converted into polygons using Intel's OpenCV computer vision library. Our analysis then proceeds independently for the two kinds of images.

Segmentation

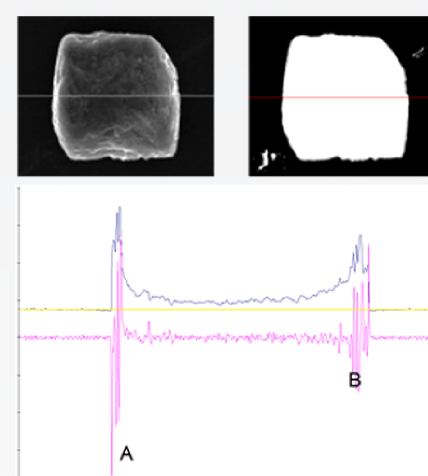
Using a global threshold to segment the particles in monochromatic SEM images can isolate internal areas of a particle useful for textural analysis. Standard edge detectors can fail to disambiguate internal texture features from particle holes if not parameterized correctly. However, user parameterization can be troublesome for automated analysis. Therefore, we have developed a segmentation technique that combines an adaptive threshold algorithm with an edge detector filter to separate a particle from a noisy background.



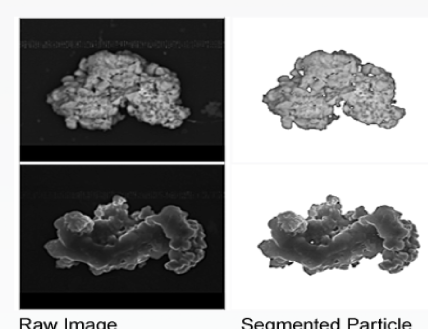
Many SEM images have bimodal pixel intensity distributions, as shown here. The first peak in the lower pixel intensity range can accurately describe background pixel intensities. Signal is often defined by the second peak at higher pixel intensity ranges. The minimum point between these two distributions can make for a suitable threshold and can be found with no user parameterization.



The adaptive threshold technique outperforms the global threshold approach. Unfortunately, some areas in the particle still fall below the discovered cutoff threshold. Here we see internal areas of the particle that are clipped by the adaptive threshold approach.

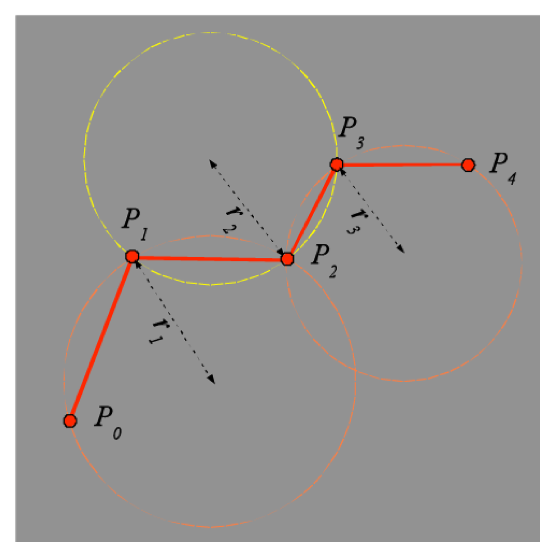


The adaptive threshold is then combined with gradient values calculated using the Sobel edge detector filter. We examine raw pixel values, shown in blue, at a single scanline shown as a red line on the SEM images. Internal areas of the particle fall dangerously close to the discovered threshold, shown in yellow, making it hard to disambiguate internal parts of a particle from holes. However, gradient values, shown in pink, define the external edges of the particle, marked by A and B.



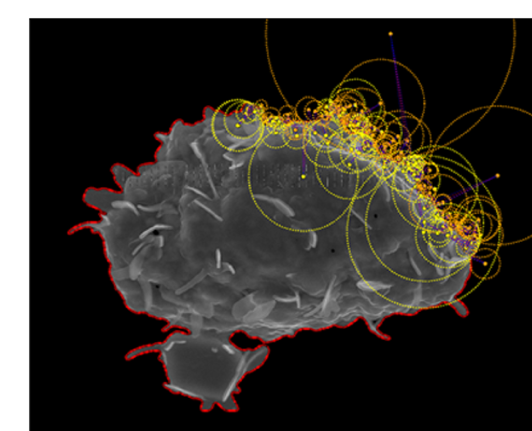
By combining the threshold and gradient information, we can distinguish internal texture features from background. This leads to an improved result shown by the segmented particle.

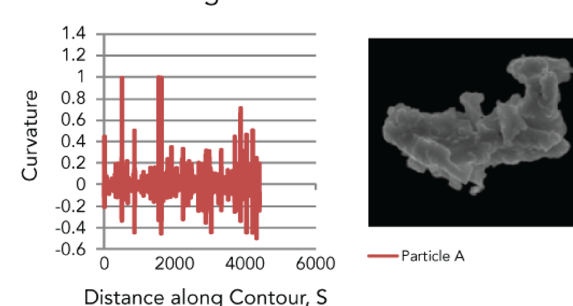
Shape Analysis



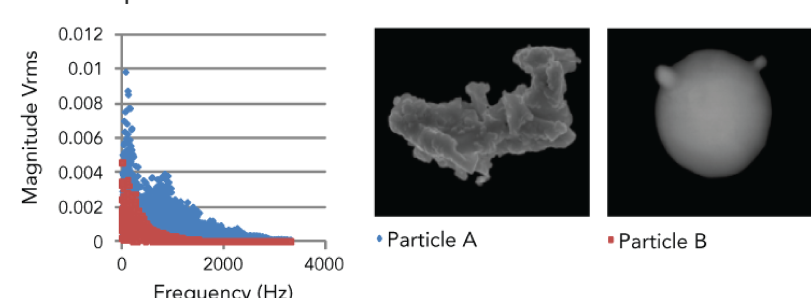
We assume a polygon (a part of which is shown here in red) samples a smooth curve. Every three points along it define a circle. We compute this circle's radius. The reciprocal of that radius is by definition the (sampled) curvature at the midpoint. If the points "turn left", the curvature is positive (the circle shown in yellow). If they "turn right", it is negative (the circle is shown in orange). If the points are collinear, the curvature is zero.

A particle's contour is polygonized using the Teh-Chin method provided by the Intel OpenCV computer vision library. As shown here, the polygon is overlaid on the particle. By traversing the polygon, we can calculate the signed curvature value at each vertex using two adjacent vertices.





Given a set of discrete, but non-uniformly spaced, samples of curvature as a function of distance along the particle's silhouette, we wish to examine $K(\nu_s)$, the Fourier transform of the curvature in terms of spatial frequency ν_s. Because that transform requires uniformly-spaced samples, however, we must re-sample the data, so we interpolate the data with cubic B-splines which we then sample uniformly (at a power-of-two resolution) and pass to a standard Fast Fourier transform (FFT) routine.



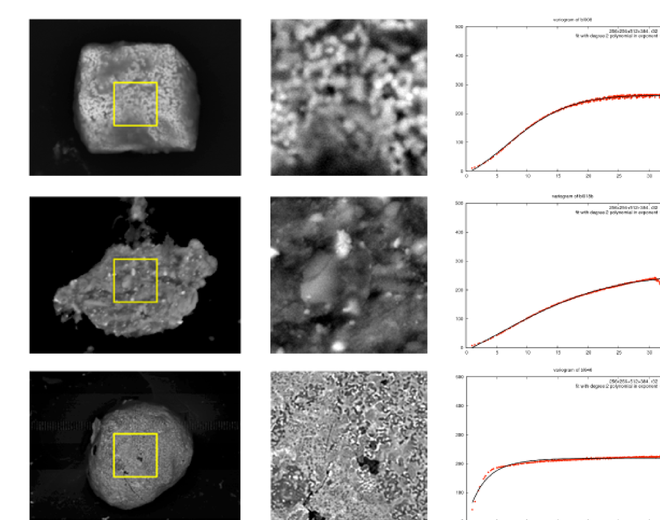
The power spectrum, $K(\nu_s)$, of $k(S)$ qualitatively shows both shape and roughness: more power at low frequencies indicates variation in shape; more power at higher frequencies indicates a rougher silhouette. By defining filters (low-, band-, and high-pass) over various frequency ranges to convolve with $k(S)$ we can yield a set of parameters that numerically characterize the shape and roughness.

Texture Analysis

Analysis of backscatter images focuses on the (visual) texture, which is the result of both composition and geometry. Using the silhouette as a boundary, we compute the variogram, a statistical measure of inter-pixel covariance as a function of distance. Variograms take on characteristic curves, which we fit with a heuristic, asymptotic function that uses a small set of parameters.

A particle's internal composition affects the visual texture of its backscatter SEM (BSEM) image. The samples shown here demonstrate the variation of texture. To quantify this variation, we first compute that image's variogram, a statistical procedure which measures pixel-pixel covariance as a function of distance between pairs of pixels. Each red dot represents a distinct inter-pixel distance.

As seen here, variograms tend to be smooth functions and distinct for different materials. This suggests a second step: dimension reduction. Fitting the variogram with a set of N parameters ($N = 4$ in this case) allows us to represent the texture as a point in N-space.



Classification

By integrating discrete overlapping bands of a particle's power spectrum we can reduce its silhouette to a few parameters. These descriptors can identify distinct shape features. By using the fit parameters from the variogram analysis, we can quantify distinct material differences among particles.

The combination of both shape and variogram fit parameters forms the basis of a multidimensional classification space whose dimensionality we may reduce by principal component analysis and whose region boundaries allow us to classify new particles on both shape and texture. This classification analysis is performed without *a priori* knowledge of other physical, chemical, or climatic properties.

Summary

We have developed a technique to automatically segment particles from both secondary and backscatter SEM images. The resulting sub-image used for both textural and shape analysis. We are exploring ways to parameterize both shape and texture. Our methods allow us to reduce a large problem space to a smaller one without user parameterization. This is useful for automated analysis of large quantities of SEM particle images. Furthermore, we can encompass multi-particulate images through modifications in our segmentation algorithm.

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