Using a commercial X-ray tomography instrument, we have obtained reconstructions of a graded-index optical fiber with voxels of edge length 1.05 \( \mu m \) at 12 tube voltages. The fiber manufacturer created a graded index in the central region by varying the germanium concentration from a peak value in the center of the core to a very small value at the core-cladding boundary.

Operating on 12 tube voltages, we show by a singular value decomposition that there are only two singular vectors with significant weight. Physically, this means scans beyond two tube voltages contain largely redundant information. We concentrate on an analysis of the images associated with these two singular vectors.

The first singular vector is dominant and images of the coefficients of the first singular vector at each voxel look similar to any of the single-energy reconstructions. Images of the coefficients of the second singular vector by itself appear to be noise. However, by averaging the reconstructed voxels in each of several narrow bands of radii, we can obtain values of the second singular vector at each radius.

In the core region, where we expect the germanium doping to go from a peak value at the fiber center to zero at the core-cladding boundary, we find that a plot of the two coefficients of the singular vectors forms a line in the two dimensional space consistent with the dopant decreasing linearly with radial distance from the core center. The coating, made of a polymer rather than silica, is not on this line indicating that the two-dimensional results are sensitive not only to the density but also to the elemental composition.
I. INTRODUCTION

Although originally X-ray computed tomography (CT) produced monochromatic images (Hounsfield, 1980), it was recognized early on that the underlying physical process was more complex (McCullough, 1975) (McDavid, 1975). Alvarez and Macovski (Alvarez, 1976) proposed a decomposition of the attenuation as a function of energy and material into a two-dimensional space with a physical motivation: one term was the photoelectron interaction with the atom and the second term was related to interactions of the X-rays with individual electrons, i.e., Compton scattering. Recently, Alvarez has quantified the size of a potential third dimension and concludes that while it exists in principle, it would be very difficult to extract in the case of medical imaging (Alvarez, 2013). The $\rho Z$ projection to density $\rho$ and atomic number $Z$ is a widely used representation of the results of dual-energy reconstructions (Heismann, 2003).

Early applications of dual-energy tomography were in medicine (Genant, 1977) (Dichiro, 1979), which remains the dominant area. Applications using microfocus techniques for rock porosity came twenty years later (Van Greet, 2000). Recently, dual-energy microtomography with a tube source of rock samples was performed with 25 $\mu m$ voxels (Teles, 2016) and dual-energy microCT with a spatial resolution of 24 $\mu m$ was used to differentiate lead and gold regions in a gold ore sample (Maier, 2017).

Distinguishing between different materials with high-resolution using more than one tube voltage is difficult because the images obtained from each tube voltage are quite similar to each other. Here, we report on multi-energy microtomography from a tube source with a voxel size near 1 $\mu m$. Even better spatial resolution, 200 nm, between different material phases in dual-energy tomography has been reported using synchrotron radiation in a study of small particles collected from an asteroid (Tsuchiyama, 2013).

The key to distinguishing between different material components with high-spatial resolution is spatial averaging, which can improve resolution of a second highly noisy component. In a related technique, geospatial imaging, a high-spatial-resolution panchromatic image (i.e., a black-and-white image) is recorded together with images with lower spatial resolution but high spectral resolution. This technique is widespread and known as pan or panchromatic sharpening (Thomas, 2008) (Ghassemian, 2016).

The application of pan-sharpening to microCT is more recent. For example, 88 $\mu m$ pixels of an energy-integrating detector have been combined with a second, orthogonal imaging photon counting X-ray detector with 1 mm x 1.4 mm pixels and 4 energy bins to produce piecewise constant maps of regions containing elements such as iodine and barium (Clark, 2015). The subject of the study was a mouse injected with contrast agents. In a follow-on experiment, a spatial resolution of about 200 $\mu m$ was achieved in work showing the elemental decomposition of tumors (Clark, 2017).

For the purpose of this paper, we needed to be able to identify regions in the images that we expect to be similar. However, our sample is an optical fiber. This has a rotational and translational symmetry that makes the identification of these similar regions relatively straightforward.

Optical fibers are, of course, of great technological interest and X-ray CT of optical fibers has been the subject of several recent papers. A photonic band gap optical fiber (Sandogchili, 2014) and optical fibers embedded in a carbon-fiber reinforced polymer (Chiesura, 2015) have been studied with X-ray CT. Dual-energy X-ray tomography with 0.5 $\mu m$ voxels has been used to observe Ge in the core of spliced optical fibers using synchrotron radiation tuned to the Ge K-edge (Koike, 2013). Although the graded-index optical fibers we study here are a commercial product, the development of optical fibers remains a research topic. Closely related to the germanium-enhanced cores we study here are single crystal germanium-core optical fibers (Xiaoyu, 2017).

Other authors have presented methods to reduce noise in the smaller second component found in dual energy CT. In the context of medical CT, recent work includes Petrongolo and co-workers (Petrongolo, 2015 and Harms, 2016), who combined CT images taken with different tube voltages with a regularization term resulting in an order of magnitude reduction in noise compared to straightforward image subtraction. Xue and co-workers (Xue, 2017) imposed regularization and edge-preserving constraints to reconstruct a few basis materials per voxel, and Li and co-workers (Li, 2018) emphasized edge-preservation and redundant information in multi-energy reconstructions. In the context of geology, recent work includes that of Paziresh and co-workers (Paziresh, 2016) and dual-energy microCT with a spatial resolution of 24 $\mu m$ was used to differentiate lead and gold regions in a gold ore sample (Maier, 2017).

The aim of this study is to start with multi-tube voltage X-ray CT measurements of the optical fiber and use singular value decomposition (SVD) to determine the size of the lower dimension subspace that mainly defines these results. We will use geometric spatial averaging over that subspace to decrease the noise of the smaller SVD component and increase the resolution of distinguishing how material phases vary across the cross-section of the optical fiber. This is the main contribution of this study. We want to see how material aspects of the optical fiber appear quantitatively in the coefficients that arise from the singular value decomposition process.
II. MATERIALS AND METHODS

Using a Zeiss Versa XRM-500 microCT (Zeiss, 2016), we studied a graded-index optical fiber, ThorLabs GIF625 (Thorlabs, 2016). The sample contains a germanium-doped silica core with nominal diameter of 62.5 µm, a silica cladding with a nominal diameter of 125 µm, and an outer acetate coating with nominal diameter of 245 µm. These layers are concentric within a small uncertainty.

A piece of the fiber was securely fastened to the end of a 3 mm diameter aluminum nail, and the other end of the nail was placed into a pin-vise sample holder. The source-to-sample distance was 16 mm, and the detector-to-sample distance was 25 mm. A 20x optical lens was used. In the Versa, the scintillation material in the front of the optical lens creates visible photons from the X-ray photons, which are collected by the optical lens and focused on the optical CCD (charge-doubled device) detector, giving extra magnification for a given source-sample-detector arrangement. Output from the 2048 × 2048 pixel optical detector was binned so that each 4 × 4 array of pixels was averaged and read as a single pixel, which increased the signal-to-noise ratio of the projection images. For each tube voltage used, 1601 projection images were acquired at rotations uniformly spaced over 180°. A filtered back projection algorithm was used for the reconstructions. After reconstruction, this resulted in approximately 500 cross-sectional images of about 500 × 500 pixels per slice.

Grey-scale reconstructions were performed at 12 tube voltages, namely (30, 35, 40, 45, 50, 60, 70, 80, 90, 100, 120, 140) kV with 1.05 µm cubic voxels. We note that saying the tube voltage was 90 kV, for example, means that the maximum energy X-ray photon was 90 keV and most were of lesser energy. The sample was not moved when changing tube voltages. The linear spatial resolution was about 2 voxels or 2 µm. The exposure dose was (1.192, 0.8531, 0.6764, 0.4718, 0.3615, 0.2249, 0.1452, 0.1141, 0.0890, 0.0902, 0.0749, and 0.0747) mAs for the voltages, respectively. These values produced similar count rates for white-field images (i.e., images with no sample present). A typical reconstructed slice is shown in Fig. 1, for the tube voltage of 100 kV. Reconstructed slices using other tube voltages are not shown, since the same slice using different tube voltages appear very similar to the naked eye. The numerical analysis described in this paper makes use of small differences between images that the eye would miss.

The light and dark rings at the core-cladding and cladding-coating boundaries are due to propagation-based phase contrast (Wilkins, 1996). In fact, such effects have been observed on an instrument very similar to the one used here (Bidola, 2015). Propagation-based phase contrast is an important way to distinguish, in X-ray CT, between different areas of a sample (Gureyev, 2009), especially in cases where boundaries between phases are important or at crack surfaces or between materials that have similar X-ray attenuation (Mayo, 2012). In the optical fiber, while the dark and light rings caused by propagation-based phase contrast are useful for clearly delineating the core, cladding, and coating regions, we are only interested in the contrast between bulk phases caused by elemental makeup and elemental gradients in the core region. We therefore avoid the regions close to these light and dark rings when sampling and averaging the gray-scale values of pixels. In recent work on phase contrast dual-energy imaging, this strong phase contrast was confined to a small region near boundaries between materials (Li, 2018) (Yu, 2016).

The lower tube voltages were used to see if there were observable effects of the Ge K-edge at 11.103 keV (Williams, 2001). All 12 voltages were used to test whether a reduced-dimensional representation of the dependence of the reconstructed images on tube voltage could be observed experimentally. Since we did not know the value of this reduced

![Figure 1. Reconstruction of the graded-index optical fiber with a tube voltage of 100 kV with the core-cladding, cladding-coating, and coating-air boundaries visible. There also is an internal coating-coating boundary probably reflecting the formation of the coating from two layers of the same material. Radial rings on the right show where pixels were collected for analysis from each slice.](image-url)
TABLE I. The annular regions were numbered starting from the innermost to the outermost. The numerical labels of the annular regions belong to each component of the optical fiber images (core/cladding, coating, air) are listed.

<table>
<thead>
<tr>
<th>Component</th>
<th>Annular Region Labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core</td>
<td>1-14</td>
</tr>
<tr>
<td>Cladding</td>
<td>15-23</td>
</tr>
<tr>
<td>Coating</td>
<td>24-30</td>
</tr>
<tr>
<td>Air</td>
<td>31-35</td>
</tr>
</tbody>
</table>

TABLE II. Singular values \((\sigma_1, \sigma_2, \sigma_3)\) are given as a function of the number of slices used in the average. The first singular value is normalized to 1 in all cases. Because the 51 slice case has the minimum third singular value, this number of slices was used in our analysis.

<table>
<thead>
<tr>
<th>Number of Slices</th>
<th>(\sigma_1)</th>
<th>(\sigma_2)</th>
<th>(\sigma_3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.00085</td>
<td>0.0017</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>1.00085</td>
<td>0.0016</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>1.00085</td>
<td>0.0015</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>1.00084</td>
<td>0.0015</td>
<td></td>
</tr>
<tr>
<td>51</td>
<td>1.00086</td>
<td>0.0014</td>
<td></td>
</tr>
<tr>
<td>101</td>
<td>1.00090</td>
<td>0.0015</td>
<td></td>
</tr>
<tr>
<td>201</td>
<td>1.00094</td>
<td>0.0015</td>
<td></td>
</tr>
</tbody>
</table>

dimensionality \textit{a priori}, we used 12 tube voltages, thought to be more than enough to define this reduced dimensionality. We did not see evidence of the Ge K-edge. The reduced-dimensional representation of the reconstructed images is discussed below.

The actual pixel values of the core and the coating regions were estimated and the minimum voxel intensity values in both the horizontal and vertical directions, where the image had a dark boundary ring (as seen in Fig. 1) due to propagation-based phase contrast, were located. The centers were placed at the average of these outer boundaries. Then pixel intensities were collected based on their distance from each center in each slice in concentric annular regions. The correspondence of the numerical labels of these annular regions to the visual components of the optical fiber images are listed in Table I. The same annular regions, averaged over many slices, were used for each voltage. Some of these radial ring annuli are shown in Fig. 2.

For each tube voltage, we analyzed pixel intensities from a maximum of 201 slices of optical fiber, chosen around the center of the reconstruction. This limitation was chosen to minimize cone beam artifacts. We then averaged the intensity of the voxels in each of the 201 slices, and subsets of these 201 slices, at 30 different radii from the center of the fiber, covering all three geometric regions, and 5 more taken from the surrounding air. For each radius, we collected individual pixel intensities that were within 1 voxel length \((1.05 \mu m)\) of the given radius for each tube voltage. These 30 radii were chosen to sample all the expected material phases, with proportionally more assigned to the core region to try and recover the expected gradient in germanium content.

An average over the outer five radii (see Fig. 2) located in the air surrounding the optical fiber gave the air-voxel intensity for each tube voltage, which was subtracted from each average intensity for core, cladding, and coating annular regions. The ratio of the standard deviation to the mean grayscale varied between 1 % and 3 % in each slice.

### III. RESULTS

#### A. Singular Value Decomposition

We formed a data matrix with real elements \(X_{rv}\) in which \(r\) runs over 30 values of the radius (excluding the five annular regions) and \(v\) runs over the 12 tube voltages. We wished to determine how many tube voltages were necessary for this study, or in other words, we wanted to determine the dimensionality of the subspace that accurately represented these results. In order to understand this dimensionality, we performed a singular value decomposition (Golub, 1983) (SVD) on the data matrix into

\[
X = U\Sigma V^T
\]

where \(\Sigma\) contains the singular values \(\sigma_i\), and \(U\) and \(V\) contain the left and right singular vectors respectively. \(U\) is a \(30 \times 30\) orthogonal matrix, \(\Sigma\) is a \(30 \times 12\) diagonal matrix with non-negative entries, and \(V\) is a \(12 \times 12\) orthogonal matrix. For readers more familiar with principal component analysis (PCA), we note that the right singular vectors \(V\)
in SVD are the same vectors which appear in PCA and the squares of the singular values in SVD are the eigenvalues of PCA. PCA has a long history in X-ray tomography (Weaver, 1985). If the singular values are normalized so that the largest value equals unity, then we choose to define the dimensionality of the subspace by the last singular value to be considered that still remains above about 0.002. Using only these singular values and vectors, the original data matrix can be reconstructed within small error, indicating that only this number of tube voltages was necessary for the collection of data.

The last row of Table II shows the first three singular values, denoted by \( \sigma_1 \), \( \sigma_2 \), and \( \sigma_3 \), for the full 201 slice average. The entire process was repeated by averaging over a subset of these 201 slices, also shown in Table II. The value for the second singular value seems to stabilize for the number of slices below 101, which we interpret as getting rid of cone beam artifacts by reducing the number of slices. However, averaging over more slices should give better results, in principle, so that we regard the 51 slice values as the most reliable. It is interesting that the second and third singular values are fairly insensitive to the number of slices averaged. In further analysis, we neglect the third and higher singular values, since they are less than 0.002, along with their associated singular vectors, retaining only the first two singular values and singular vectors.

As a numerical check on the singular values obtained from real X-ray CT data, we generated unfiltered tungsten tube spectra for the same 12 experimental tube voltages using the TASMICS code (Hernandez, 2014) as well as absorption coefficients as a function of photon energy for germania, silica, and acrylate from XCOM (Berger, 2016). The absorption coefficients were averaged over the spectra produced by the TASMICS code after weighting by photon energy to account for detector response. The result of the procedure is the spectrally averaged attenuation coefficients. These coefficients form a \( 3 \times 12 \) matrix indexed by the three materials and the same 12 tube voltages as were used experimentally. The first three singular values of the matrix were determined similarly as were the experimental values, and were found to be 1, 0.0202, and 0.0002, after normalizing all three so that the first singular value equaled unity. These values are in qualitative agreement with the values we obtained experimentally in Table II, which is encouraging as a support to our analysis. The TASMICS value of the second singular value is higher than that obtained experimentally, but it was not expected to exactly equal the experimental value, since the optical fiber material structure is more complex than pure germania, silica, and acrylate. Additionally, we have neglected the unknown filtration of the tube.

**B. Need for Spatial Averaging**

The ratio of the first and second singular values (approximately 100 here) gives the noise amplification of the second singular vector in the reconstructed image compared to the first (Hansen, 1990). To compensate with counting statistics, the square of this number, i.e., \( 10^4 \), additional counts are required. Here, we obtain the extra counts by binning cylindrical shells. The number of pixels binned ranges from 5712 for pixels collected from the innermost annulus to 138 720 in the outermost annulus for the present data set. Only the smallest two annuli close to the center of each set are represented by less than \( 10^4 \) values. In contrast, using the third singular vector would require an average over \( 10^6 \) voxels, which are not available in our scans, which is a practical reason to define the dimensionality of the data to equal 2.

In every voxel, we consider the 12 grayscale values reconstructed from the 12 different tube voltage scans to be a 12 dimensional vector of observations, obtained only after first centering the 12 images from the 12 tube voltages. The observations are dotted into the two unit vectors associated with the first two singular values to yield two coefficients, \( c_1 \) and \( c_2 \), associated with each voxel of the X-ray CT image, which are the weights associated with those vectors in creating a grayscale observation of the projection in 2-dimensional space. We look at the resulting two coefficients in a single slice.

In Fig. 3, we show the resulting coefficients of the first and second singular components on a line through the center of the optical fiber (the line is shown at the bottom left of the right-hand graph) using a single slice from the center of the fiber image stack. In Fig. 3, the first singular component shows a rounded peak in the center of the fiber, indicating the change in the amount of Ge radially through the fiber center, and two plateaus, one in the silica cladding and one in the acrylate coating, indicating their chemical uniformity. Narrow peaks due to propagation-based phase contrast effects are also seen at the optical fiber phase boundaries. In contrast, the second singular component appears to be simply noise except for these same narrow, but much smaller, propagation-based phase contrast region peaks. Note the \( 10^4 \) difference in vertical scales between the two plots in Fig. 3.

Another view of the noise inherent in the values of \( c_1 \) and \( c_2 \) is shown in Fig. 4. For this figure, 5000 pixels were chosen randomly from a number of annuli in the core, cladding, and coating phase, with an equal number taken from each annulus, and the values of \( c_1 \) and \( c_2 \) were plotted for each annulus. The second moments of each of the 5000 data point sets are represented by an ellipse in Fig. 4. While the coefficients of the first singular vector were mostly distinct from each other from region to region, as shown by the separation of the ellipses along the horizontal \( c_1 \) axis,
Figure 2. Radial rings on the same slice of data to show where pixel intensities were collected. Every other annulus through the core and cladding is left out of this image for clarity. Shown are regions: 1,3,5,7,9,11,13 (core), 15,17,19,21 (cladding), 24-30 (coating), 31-35 (air).

Figure 3. Intensity of the first (left plot) and second (right plot) singular components on a line through the center of the optical fiber. The line is shown on the image, which is inset at the bottom left of the 2nd plot. Peaks due to the propagation-based phase contrast effect are seen at the material boundaries. Note the $10^4$ difference in the vertical scales between the left and right images.

The coefficients of the second singular vector are spread along the vertical $c_2$ axis, indicating that there were many values of $c_2$ for each distinct value of $c_1$. Nevertheless, by accumulating a sufficient number of independent samples, meaning the annular regions, and averaging over a number of slices, distinct values of the coefficient of the second singular vector can be associated with various regions, as will be shown in Fig. 5.
Figure 4. The distributions of the sampled points are shown. The ellipses contain 90% of the 5000 data points used at each location. Half of the annuli are shown for the core (annuli 1,3,5,7,9,11), cladding (13,15,17), and coating (24,26). Note that the ellipse fits for the cladding and coating annuli closely overlap each other. The annulus number of the ellipses increases from right to left.

Figure 5. Annular averages of the coefficients of the first two singular components are plotted starting from the center of the fiber and continuing radially outward. The averages are labeled according to the numbering of the annuli from which the pixel intensities came, as given in Table I, where every other core/cladding ring (1-23) is shown, and then all rings labeled (24-30). The outer rings were collected to obtain an air value. Regions are labeled where image pixels from the central core, the cladding, and the coating are projected onto this plot. The colors of the labels correspond to the colors in Fig. 6.

C. Discussion

The coefficients of the first two singular vectors, averaged over each annular region, are plotted in Fig. 5 as pairs of $(x,y)$ points for all 30 angular regions. The horizontal axis is for $c_1$ and the vertical axis is for $c_2$. Each point is labeled as to which annular region over which it was determined. The core, cladding, and coating regions are also labeled, with the color of the fonts corresponding to Fig. 6 below. Fig. 5 uses both singular value coefficients to reveal material information about the optical fiber, not just gray scale values and visual distinction between components. An average has been made over the same 5000 voxels used in Fig. 4, chosen from each annulus over a set of 51 slices at each tube voltage. Remember that the annuli labels increase from the core radially, so that #1 is at the center of the core and #30 is near the outer edge of the coating. With the increasing labels indicating a progression from the core outwards, Fig. 5 shows a linear progression across the core where the germanium concentration is highest in the center and the doping concentration is supposed to be reduced to zero by the edge of the core. The cluster of points...
located in the cladding region essentially show the same behavior as was seen in Fig. 3 — a nearly constant value of the first singular value coefficient in this region. The random vertical positioning of these points simply indicates the noise in the second singular value, as in Fig. 3, but reduced by averaging. The cladding should be essentially the same material as the core (without Ge), silica, so the linear trend in the core points blends right in with the cladding points, as would be expected.

The variation in the second singular coefficient in the acrylate polymer coating region also has the character of the noise seen in the right plot of Fig. 3. The first singular value coefficient value for the coating is smaller than that for the cladding. We expect the coefficient of the first singular component to be much lower in the polymer than the silica due to its lower density as well as its lower atomic number. However, the change from silica to polymer is qualitatively different than the change from core to cladding via the reduction of the germanium doping, since the second singular component coefficient for the coating is near \(-1 \times 10^6\), which is quite different from a simple linear extrapolation of the linear regime in Fig. 5, which would give about \(-6 \times 10^6\). This demonstrates observation of a material-dependent effect at the micrometer scale via the coefficients of the two principal singular values.

In order to more clearly visualize the changes in material components represented by the changes in the two principal singular value coefficients, we used the coordinate axes in Fig. 5 and formed a triangular region that closely encompassed the data points in this figure. The endpoints of the triangular region were core \((7 \times 10^{10}, 5 \times 10^6)\), cladding \((3 \times 10^{10}, -3 \times 10^6)\), and coating \((0 \times 10^{10}, -1 \times 10^6)\). Then for the same single slice of data used for Fig. 3, each pixel, with its two values of \(c_1\) and \(c_2\), was colored according to its position on Fig. 5, where the red, green, and blue color channels were assigned according to the inverse distance from each point to the three vertices of the triangle (red - distance to the core endpoint, green - cladding endpoint, and blue - coating endpoint). The resulting image is shown in Fig. 6, where the inner core region is red since the data points are close to the core triangular endpoint, with the cladding mostly green and the coating mostly blue. Fig. 6 demonstrates that by using spatial averaging, we can separate the three materials of the optical fiber into three distinct material regions, as a projection of the first two singular vectors of the matrix of averaged intensities.

By averaging over the voxels in an annulus and a number of slices, we were able to enhance the signal-to-noise ratio of the second singular component and make it visible at a small spatial scale, clearly displaying material differences in the sample. Although our sample had approximate cylindrical symmetry, which made it a particularly simple case for analysis, in general, the paradigm of dividing the primary monochromatic image into meaningful regions and extracting information from grouped voxels should be an effective method for enhancing the signal-to-noise ratio of the second component. In particular, images may be segmented using the first singular component and then averages
within each region may reveal additional information beyond the gray scale values, such as material composition, using the second singular value.

IV. CONCLUSIONS

Multi-voltage X-ray tomography has been demonstrated using an X-ray tube source with 1.05 µm voxels, 2 µm spatial resolution, and 12 tube voltages. A singular value decomposition analysis revealed that the results spanned a two-dimensional subspace. In other words, although we used 12 tube voltages, dual-voltage tomography (i.e., tomography with only two tube voltages) would have yielded substantially identical results and a third tube voltage would not have been nearly as informative. This is of course assuming that the two tube voltages were separated enough so that there was some difference in contrast mechanisms between the two voltages. We averaged over regions in order to reduce the noise and to be able to see the second singular component within each region, a technique which may be important in other applications.

Although the spatial averaging technique was necessary to see the second singular vector at high spatial resolution, the second singular vector will always have a much lower singular value and so will be noisier. The idea of using information gained from the first singular vector to partition the reconstruction before spatial averaging, also known as pan-sharpening, is an attractive alternative to pixel-by-pixel image subtraction to bring out an otherwise difficult-to-detect material contrast. We are not aware of other publications which report on pan-sharpening in microtomography at a spatial resolution as fine as the one in this paper.

The projection of image intensities into a 2-dimensional space demonstrates both density and material dependent effects. By averaging over a large number of voxels, we were able to see the density- and material-dependent effects over the noise of individual voxel variations. Projection of intensities from different material layers into the 2-dimensional space was not just the result of a 1-dimensional density effect. Projection of an entire image slice into this 2-dimensional space indicated the presence of three distinct material regions on the 2-dimensional plane, which we saw by coloring the image based on each pixel's location in the 2-dimensional space.

V. CITATIONS


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VI.

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