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Simultaneous Tracking and Registration in SiC/SiC Serial Section Images

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Serial section data is acquired by (1) sectioning, (2) surface preparation, and (3) imaging. Often, the imaging apparatus or the sample must be moved periodically, creating registration errors in the as-acquired images. For fiber composites, cross-correlation[1] is problematic because many local maxima are produced, often requiring human interaction to manually perform problematic sections. Fiducial marks are often used to mitigate this problem, but require extra work during acquisition. In this work, we develop an unsupervised technique that combines the tracking and registration processes into a single algorithm that eliminates the need for cross-correlation or fiducial marks. The algorithm is iterative, alternating between tracking and registering, optimizing both steps simultaneously, and giving fully tracked fiber architectures.

For this study, a series of serial section images, Figure 1, of a continuous SiC fiber reinforced SiNC matrix ceramic matrix composite (CMC), S200 (www.coiceramics.com/nonoxidepg.html), were obtained by automated serial sectioning with RoboMet.3D^{TM}(UES, Inc.) with a nominal pixel size of 0.5μ and an inter-section distance of 1μ. Fiber centers were detected with a modified Hough transform[2] to give fiber centers, section by section. The accuracy of detecting the centers was estimated to be 94%.

The algorithm developed is summarized in Algorithm 1. We assume that there is a 'true' location of each fiber and that the detected position differs from the true position because of (1) noise in the detec-tion algorithm, (2) false negative and false positive detections, and (3) the shift due to misregistration. We have addressed the first two of these in other publications[1, 3], and address the third here.

We model this with a *shift vector*, $\mathbf{s}$, such that the detected position is the sum of its true position and the shift vector:

$$\tilde{\mathbf{t}} = \mathbf{t} + \mathbf{s} \tag{1}$$

where $\tilde{\mathbf{t}}$ is the detected position and $\mathbf{t}$, the true position. $\mathbf{s}$ is a *latent* variable to be estimated.

The values of $\tilde{\mathbf{t}}$ are, alternatively, corrected by the Kalman filter for consistency and by a linear regression fit for straightness (over distances on the order of the inter-section distance). The difference between $\tilde{\mathbf{t}}$ and the regression-fit centers, $\hat{\mathbf{t}}$, forms an 'energy penalty,' E, to be minimized:

$$E = \frac{1}{NK}\sum_{j=1}^{N}\sum_{i=1}^{K}\left|\left|\hat{\mathbf{t}}_i^{(j)} - \tilde{\mathbf{t}}_i^{(j)}\right|\right|^2 \tag{2}$$

where N is the number of sections, K, the number of fibers that pass the 'sanity check' of being detected in every layer, subscripts refer to fiber locations, and superscripts to sections. E is a *convex function* in $\mathbf{s}$, so it may be minimized by gradient descent to give the estimate of the shift vector, $\hat{\mathbf{s}}$, which is used to update the values of $\tilde{\mathbf{t}}$. These are fed back to the Kalman filter, and the process repeated until convergence. The tracking accuracy (MOTA)[4] and energy (E) are shown in Figure 2.

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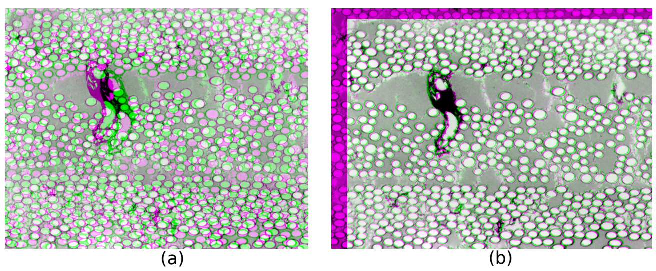

Figure 1. Two registered layers, bottom image in color. (a) As acquired. (b) registered with our algorithm.

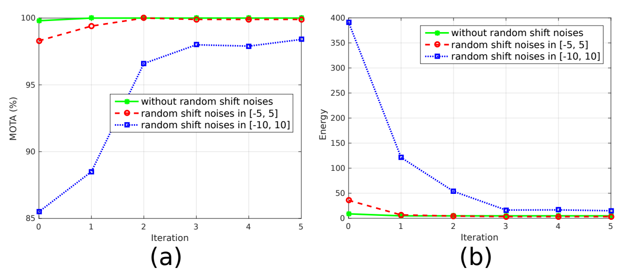

Figure 2. Algorithm performance. (a) MOTA tracking accuracy, higher values are better, (b) energy penalty E.

Algorithm 1 Simultaneous tracking and registration for an image sequence. Tracking is done with a Kalman filter with the Hungarian association algorithm[5]. a is the total number of iterations used.

$\tilde{\mathbf{t}} \leftarrow$ detected fibers on each image
for $i = 1$ to a **do**
  $\tilde{\mathbf{t}} \leftarrow$ Kalman tracked and corrected positions.
  $\tilde{\mathbf{t}}_i, i \in \{1, 2, 3, \ldots K\} \leftarrow$ sanity checked positions
  $\hat{\mathbf{t}} \leftarrow$ Linear regression fit positions
  $\hat{\mathbf{s}} \leftarrow \arg\min_{\{\mathbf{s}\}} E(\hat{\mathbf{t}}, \tilde{\mathbf{t}})$
  $\tilde{\mathbf{t}} \leftarrow \tilde{\mathbf{t}} + \hat{\mathbf{s}}$
end for

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