

A power stitching tool

Joe Chalfoun

Using a Fourier-based phase correlation method and progressively coalescing strongly-connected components permits terabytes of optical microscopy data to be assembled correctly more rapidly than previously.

For time-based studies, researchers may need to repeatedly image plates, for example of cell cultures. However, an optical microscope has a field of view smaller than a typical plate. It therefore generates a grid of overlapping partial images, and a stitching tool assembles a composite image, which may have tens of thousands of pixels per side. Stitching one such large image mosaic taxes the computing capacity of a high-end workstation. This becomes overwhelming when stitching repeat images taken over time.

High-end microscopes come with their own image stitching tool. However, these tools are often manufacturer specific and require fully-calibrated equipment, which is not always realized. An alternative is to use a manufacturer-neutral computational tool for image stitching. There are two broad sets of approaches for image stitching, known as feature-based¹ and Fourier-transform based.²

Feature-based approaches identify matching features in adjacent images and use these features to determine the extent of the overlap within the image pair. They will then use the overlap to transform the images and compose them into a single one. These approaches have gained widespread usage in consumer-oriented digital photography under the label of *panoramic photography* because they are fast and because consumers almost always take feature-rich pictures. The main drawback of these techniques is that they must use a 'segmentation method' to detect features of interest in images.

By contrast, approaches based on Fourier transforms are more computer-intensive, but can reliably handle feature-poor images. Furthermore, the computational workload is more predictable as it does not depend on the presence and detection of features in images.

Optical microscopy often has to process feature-poor images (e.g., sparsely populated cell cultures) and may be used to derive measurements (quantitative information such as counts, densities, intensities, etc.) from such images. We have developed a



Figure 1. A stitched image with 18×22 tiles and linear blending. The image has $23K \times 21K$ pixels. It has a 1GB file size.

new stitching technique that minimizes the uncertainty between overlapping areas caused by a lack of features while being nearly $500 \times$ faster than the leading alternative tool in the field.

The first step in image stitching computes translations between adjacent images using the Fourier-based phase correlation method. This produces a relative displacement and a cross correlation value for each of the tile's neighbors. We use cross correlation as a measure of the translation computation accuracy. Two adjacent images with enough texture in their overlapping area will have a cross correlation value close to 1. In contrast, the cross correlation value will be close to 0 when the overlapping area mostly consists of background or noise.

The second step assembles the tiles into a mosaic based on the computed translations. However, these translations cannot be used directly as they form an over-constrained system of equations. Our approach resolves this constraint by considering the system as a graph and progressively coalescing

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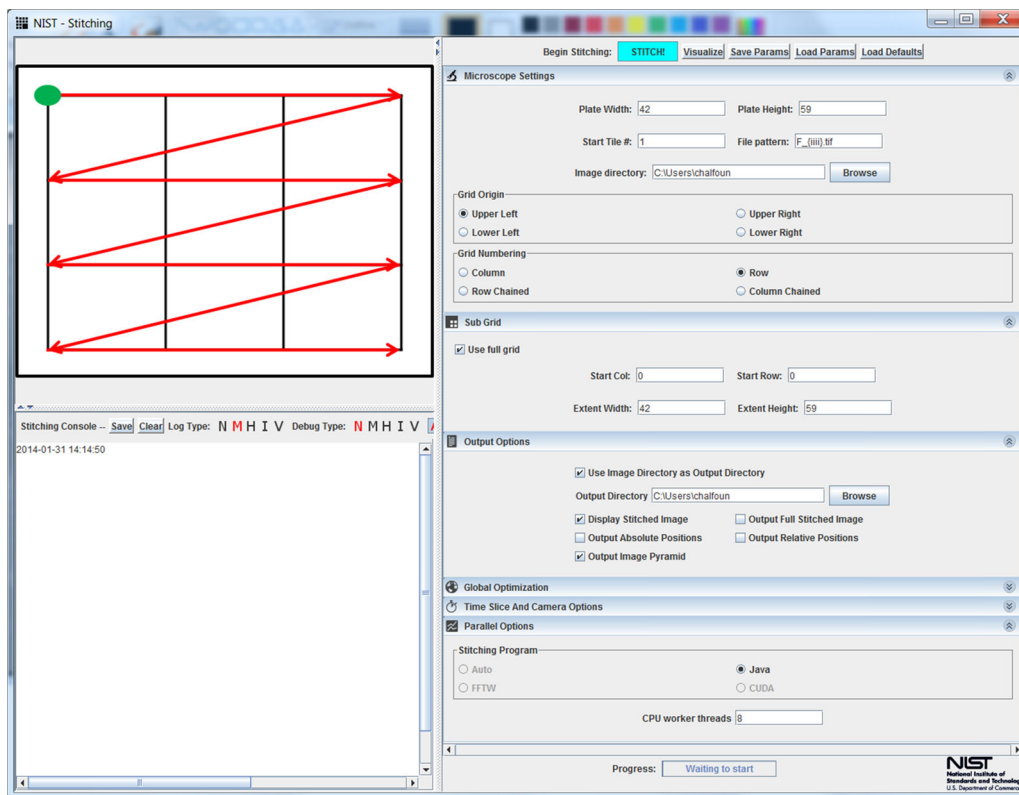


Figure 2. Image stitching graphical user interface. A user can stitch a full or partial mosaic after image acquisition. It requires very few input parameters and allows the user to visualize the stitched image before saving it to disk.

strongly-connected components. We use the cross correlation values as a measure of connection strength. This optimization minimizes the uncertainty and increases stitching accuracy. A blending algorithm is applied on the overlap area to create a smooth mosaic image: see Figure 1.

Our multithreaded implementation takes advantage of all the cores in a central processing unit to increase speed by two orders of magnitude over the leading alternative tool. Our implementation, devised for a graphics processing unit, accelerates the computation by another 5× for a total of ~ 500×. Both implementations aggressively minimize the memory footprint of the computation so it can mosaic a 50 × 50 grid in 8GB of RAM. They also generate image pyramids on the fly and allow a user to visualize their mosaics almost instantaneously: see Figure 2. These tools will be released as open source plugins to ImageJ³.

The new image stitching tool handles terabytes of optical microscopy data and minimizes uncertainty in image stitching computations. The tool mosaics a plate’s images and visualizes it at near interactive rates, thereby allowing scientists ready access to their results and giving them ample time to intervene in long running experiments. This promises to start transforming

experiments into computationally steerable ones. **Please provide a statement of next steps. This is an SPIE requirement. Only one or two brief sentences are required, but you do need to say what you are doing, rather than what could be done in general.**

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