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# High Resolution Film Scanning Reconstruction by Image Stitching and Intensity Correction

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## Abstract

*Testing at the Library of Congress and other institutions has determined that there can be greater than 3000ppi of real information in original film negatives and transparencies. This exceeds the real capture resolution of virtually all digitization systems which capture the entire film in a single image. The limitations of optics, sensors, and light restrict the effective resolution achievable in a single capture to substantially less than the information available in the original materials.*

*The aim of this project was to develop a system to combine multiple image segments acquired at very high resolutions to create a single merged image that effectively contains the total information available in the original film. There are several commercially available solutions which can be used to perform this task, however, none of those tested produced optimal results. The project was specifically focused at multi-segment monochrome capture of large format photographic negatives from the LOC Prints and Photographs (P&P) Division, however the process developed is applicable to a wide range of applications.*

## Introduction

High quality digitization in cultural heritage digitization centers often scan subjects under high resolution settings (e.g., >3000ppi) to preserve the content details. Such high resolution settings often prevent the whole frame imaging of large size subjects, thus multiple segment scanning is required to collect different parts of the film, which are then stitched together to reconstruct the complete image. This process follows the same principle as the panorama construction by stitching multiple pictures with overlapping fields of view [1, 2]. While picture panorama creation constructs a wide angle view of a physical scene, the goal of digital preservation is to accurately reconstruct the complete subject image without losing detail. For example, recently the Library of Congress obtained two Digital Transitions® scanners (Figure 1) for 4×5" negative film digitization with high resolution settings (3000, 3750, and 4000ppi). Each film has to be scanned multiple times to cover the entire frame, which are then assembled to reconstruct the complete film image.

The subject project for this research is the Farm Security Administration Safety Film collection at the Library of Congress. This is a collection of 85,000 large format black and white film negatives, which are currently being digitized to preservation standards by the Library. As a part of the planning for this effort, all digitization methodologies were considered, and significant testing and evaluation was done to identify the most optimal processes to employ. The resulting process employs 100 MP image sensors mounted on customized imaging systems which use specialized X-Y movable film carriers. As stated above, a typical final image is created from four quadrant images, each using the appropriate resolution setting of the sensor for the established project requirement.

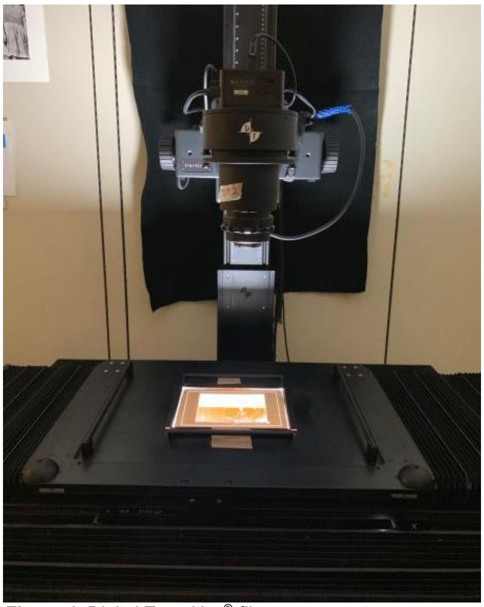


***Figure 1.*** *Digital Transition® film scanner setup*

Initial testing with image merge software from a variety of sources exposed a series of shortcomings, including imperfect segment alignment, distortion, and loss of resolution due to blending. Post-merge inspection of images revealed a high reject rate due to these issues, significantly impacting the program. In addition, all programs tested only worked with RGB capture, dramatically increasing the file size for each capture, further impacting the process. Given the massive scale of this project, we needed to find a new approach.

In this paper we present a two-step transformation-based approach to automatically stitch the four quadrant patches of each subject/film into a complete high resolution image. The first step implements geometric transformation to stitch multiple patches together. Our system first detects the texture features from each patch, and then image alignment [1] is applied to match the feature points among the patches. The optimum match determines the geometric transformation among each pair of patches. Such transformation is then applied to transform the patches to the same reference coordinate system (compositing surface), i.e., stitching patches for the complete image. The second step conducts grayscale intensity transformation to achieve a consistent illumination/exposure among different patches. In case of high contrast intensity among neighboring patches after stitching, a color/grayscale intensity adjustment approach is applied to obtain a consistent look (same exposure) of the stitched patches. With the restriction of similarity transformation (translation only), our approach introduces no geometric distortion among patches, which preserves the resolution/sharpness well when compared with a commercial software tool.

This paper is organized as follows. Section 2 briefly introduces the background of image stitching and blending technologies, and the color/grayscale correction approaches to achieve the consistent exposure visual effect. Section 3 presents our automatic stitching and intensity adjustment system to reconstruct the complete film image. Experimental results of stitching and intensity adjustment, and the resolution loss assessment are also shown in the end of Section 3. We draw conclusions in Section 4.

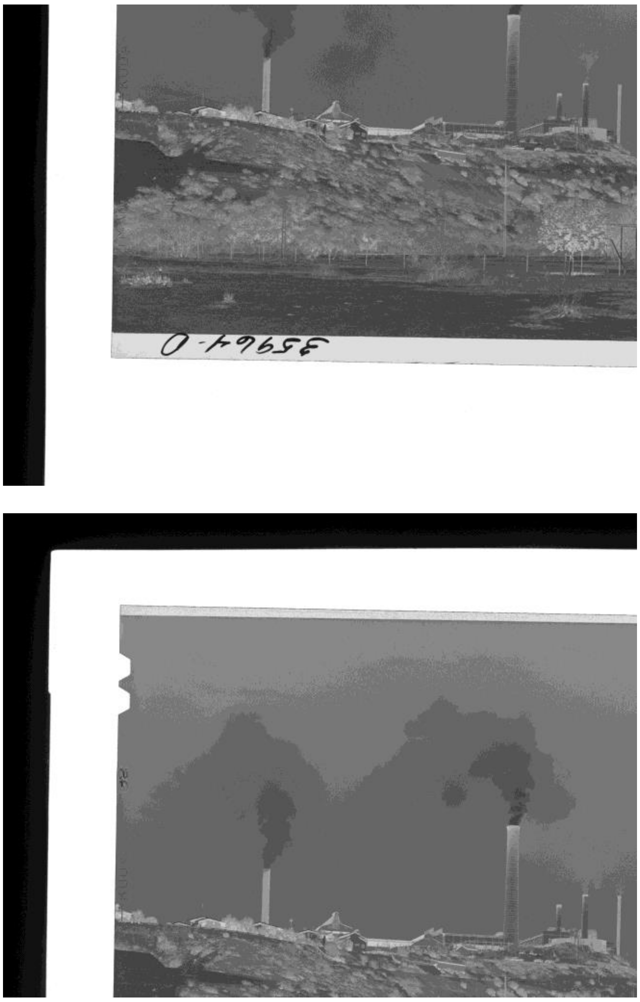
## Background

Traditional stitching approaches estimate the camera implicit and explicit parameters first [1], based on which geometric (e.g., affine or projective) transformations are used to project the images onto the compositing surface to construct the final panorama. Such approaches are usually computationally expensive and are not robust. Recent advances in image processing technology, specifically the image feature detection and extraction approaches [3, 4, 5, 6], have made possible the modern stitching algorithms that are not dependent on the camera modeling process. In particular, these local features focus on the image texture description (edges and corners), which are robust to the color/grayscale intensity variations due to the exposure changes among different views. A comprehensive review of the image features and their applications on image retrieval, object recognition and scene understanding can be seen in [7, 8]. In our system, we select the SURF [5] feature for patch stitching due to its robustness to noise and geometric distortions and transformations (translation, rotation, and scaling), and fast computation in feature extraction [7]. After the feature points identification and mapping between each pair of the patches, the corresponding geometric transformation of the patch pair can be derived by a least square error minimization method. The transformations then project the patches to the correct locations on the compositing surface to render the panorama.

The stitched patches may have intensity contrast due to different illumination or exposures, which introduces a visible seam at the boundary between the patches. Furthermore, since the texture features used for stitching are not dependent on the color or grayscale intensity, such inconsistent intensity cannot be corrected in the patch stitching/transformation process. In panorama, image blending and cloning technologies [1, 12] are often applied for a smooth transition in the boundary, such as alpha blending/feathering, Poisson blending [10], and Laplacian pyramid blending [11]. A detailed review of the state-of-the-art blending technologies can be seen in [12]. The blending technologies usually aim to smooth the stitching boundary but not for the whole patch exposure adjustment. Traditional color/grayscale intensity correction (also termed as mapping or transfer) approaches include parametric and non-parametric models. Parametric models can be divided into two categories as global [13, 14] and local [15, 16] models. Global models employ a transformation (diagonal, affine or arbitrary) matrix to map the color/grayscale intensity or histogram of one image to the other. Local models focus on the piecewise region mapping after image segmentation. Non-parametric methods [17, 18, 19, 20] assume no particular model format of the correction/transferring function. A lookup table is often constructed to directly map the full range of color/grayscale intensity levels. The lookup table may be constructed from the image feature histogram correspondence or pixel pairs in the overlapped area of two images. These approaches should be robust to the noise/outliers in the feature extraction and mapping process, and maintain the monotonicity of the color/grayscale intensity levels. For example, in [17] and [18], and [19], the transfer functions are constructed by mapping the histograms of SIFT texture feature and color/grayscale intensity. In [19], the cumulative histograms of the color/grayscale intensity are mapped between two images.

## Geometric and Intensity Transformation

The input to our model includes four quadrant patches of a film, as shown in Figure 2. The first step of geometric transformation identifies the SURF features of each quadrant patch. The common features in the overlapping areas of each pair of patches are then identified (see Figure 3), based on which the geometric transformations can be estimated using robust statistics, i.e., a RANSAC algorithm [6]. In our model, we choose one patch as the reference (e.g., the brightest patch) and identify the geometric transformations of the other three patches with respect to this reference patch. In particular, a feature matching example is shown in Figure 3, in which it can be seen that most features are correctly matched in the two patches. The outliers are removed in the subsequent RANSAC algorithm.



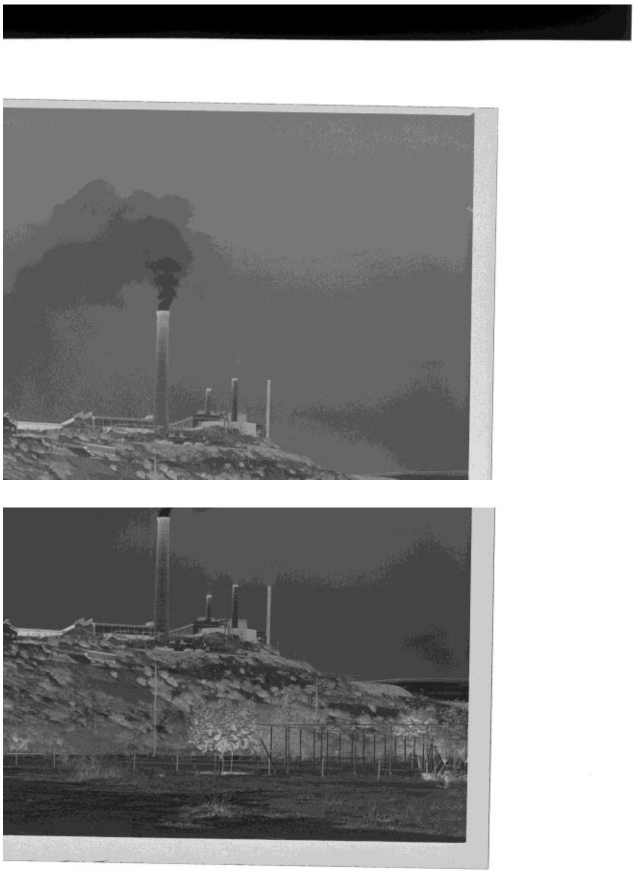


***Figure 2.*** *Four quadrant scans of a 4"×5" film*

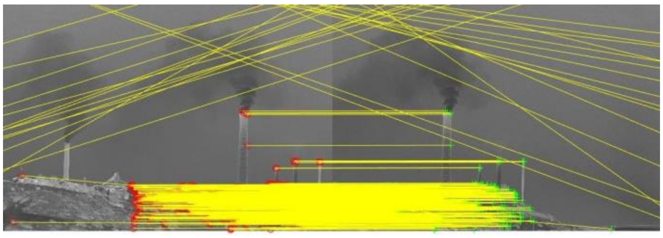


***Figure 3.*** *SURF feature extraction and mapping to stitch two neighboring patches. Red points in the left patch match with the green points in the right patch.*

Traditional geometric transformations are presented by a 3×3 matrix, which can be used to model the similarity, affine, and projective transforms [1, 2]. Projective transforms characterize the most general 2D transformation from one space to the other, which consists of eight independent parameters. Affine transforms include six free parameters, with the last row of the matrix as [0 0 1]. Affine transforms preserve parallelism and provide a good model of local deformations. Similarity transforms consist of four unknown parameters (translations in two directions, rotation angle and the scaling factor), which preserves angles between lines. For the parameter estimation, the minimum number of matched point pairs for the above three transforms are four, three, and two, respectively. In practice, a regression algorithm minimizing the least square error is applied to estimate the parameters when we have more point pairs. In our model, we apply the similarity transform to model the slow panning and minor zooming camera, which fits our system construction well. After the transformation matrix estimation, we transform the other three quadrants to the same reference space as the first one to reconstruct the complete film image. Figure 4 shows the stitched result after the geometric transformation step.

***Figure 4.*** *The stitching result of the four quadrants in Figure 1.*

After the stitching, the whole frame image may show grayscale intensity variations among neighboring patches (see Figure 4). Grayscale intensity transformation (blending or correction) technology [12] is then needed to solve this problem. For our application, we developed a piecewise gamma correction approach to adjust the intensity of all patches with respect to the reference patch. This is a local parametric model. Compared with the existing models [15, 16], our approach is easy to implement with low computational cost, which is superior to process such large size images. The final result shows a consistent exposure among patches, see Figure 5. In particular, the proposed approach first identifies the overlapping areas among neighboring patches after stitching. Using the reference patch as the target, we again derive a least square solution which fits multiple gamma correction curves at different intensity level segments (e.g., [0-50, 51-150, 151-255]) for other patches. Such piecewise intensity adjustment transforms the source patches to be the same exposure level as the reference patch. In our application, the piecewise intensity segments are identified from the overlapping area histograms. Depending on the resolution requirements, the number of intensity segments may be increased for more accurate transformation[1].

After the two-steps algorithm for the whole frame image reconstruction, we further verify the resolution degradation due to the geometric and intensity transformations. We use a film target from the Image Science Associates™ [2] to evaluate the sampling efficiency [22] values before and after the stitching and correction. Figure 6 shows the complete target image after the whole process, on which we identify all the edge regions for the sharpness assessment using our previously developed software OpenDICE [23]. We compare the sharpness losses with a commercially available software. Table 1 shows the average

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[1] We recently practiced the electronic shutter and power regulator to obtain a more consistent control over the camera settings, which also significantly reduced the exposure variations.

[2] https://imagescienceassociates.com/

sampling efficiency values (%) derived from the horizontal and vertical edges on the target before and after the stitching and correction. It can be seen that our proposed model preserves the film content details well with very close sharpness measurements as the quadrant patches.

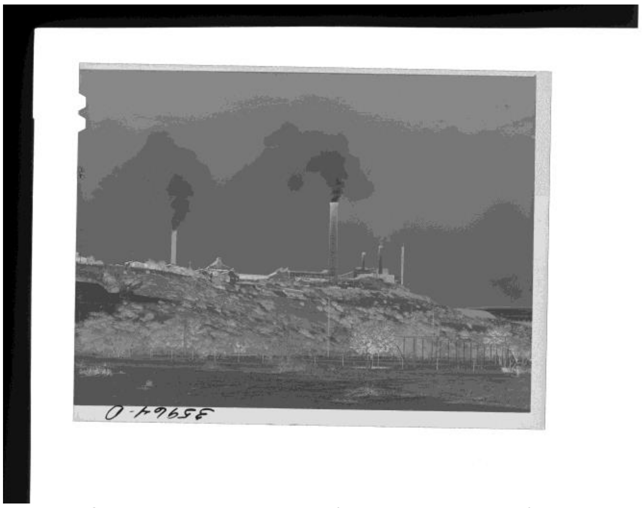

***Figure 5.*** *Grayscale intensity correction for the stitching result of Figure 4.*

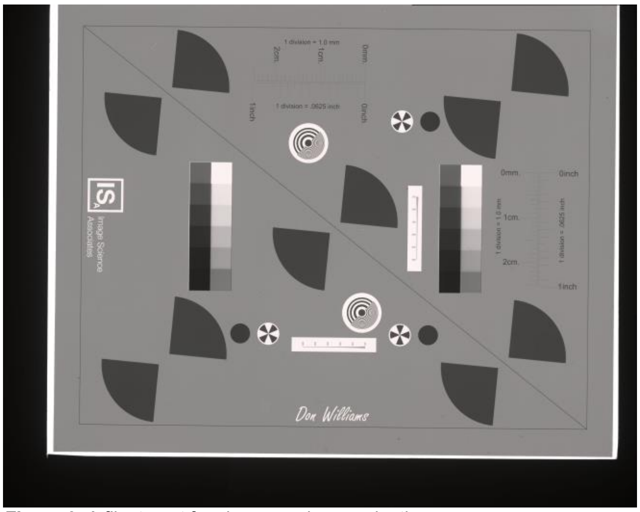

***Figure 6.*** *A film target for sharpness loss evaluation.*

| Sampling Efficiency (%) | Before stitching | Stitching by our approach | Stitching by a commercial software |
|---|---|---|---|
| Horizontal | 78 | 77 | 71 |
| Vertical | 79 | 79 | 71 |

***Table 1.*** *Sampling efficiency comparison between the before and after stitching using our approach and a commercial software*

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## Author Biography


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