Digital Analysis and Restoration of Daguerreotypes

Xiaoqing Tang[a], Paul A. Ardis[a,†], Ross Messing[a], Christopher M. Brown[a], Randal C. Nelson[a], Patrick Ravines[b], and Ralph Wiegandt[b]

[a] University of Rochester, Rochester, NY, USA 14627
[b] George Eastman House, Rochester, NY, USA 14607

ABSTRACT

George Eastman House International Museum of Photography Conservation Laboratory and the University of Rochester Department of Computer Science are researching image analysis techniques to distinguish daguerreotype plate and image features from deterioration, contaminant particulates, and optical imaging error occurring in high resolution photomicrography system. The images are captured at up to 30 times magnification and composited, including the ravages of age and reactivity of the highly polished surface that obscures and reduces the readability of the image. The University of Rochester computer scientists have developed and applied novel techniques for the seamless correction of a variety of problems. The final output is threefold: an analysis of regular artifacting resulting from imaging conditions and equipment; a fast automatic identification of problem areas in the original artifact; and an approximate digital restoration. In addition to the discussion of novel classification and restorative methods for digital daguerreotype restoration, this work highlights the effective use of large-scale parallelism for restoration (made available through the University of Rochester Center for Research Computing). This paper will show the application of analytical techniques to the Cincinnati Waterfront Panorama Daguerreotype, with the intent of making the results publically available through high resolution web image navigation tools.

Keywords: Art Restoration, Daguerreotypes, Dataset, Inpainting

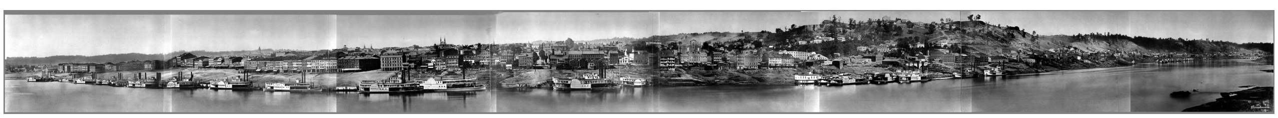


Fig. 1. The Cincinnati Waterfront Panorama Daguerreotype (as mosaic of eight plates, courtesy of www.cincinnatilibrary.org)

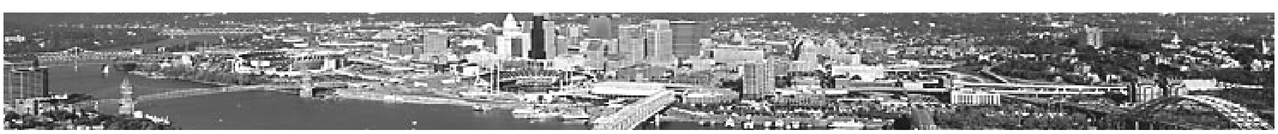


Fig. 2. Cincinnati Panorama by James Blakeway (courtesy of fabframes.wordpress.com)

1. INTRODUCTION

The daguerreotype (also written as *daguerréotype*) is the first photographic form, used to record some of the most important images of the mid-19th century. Captured in a lattice of gold-coated silver-mercury amalgam on a polished silver plate, these images are unique, cannot be duplicated, and are in danger of being lost forever.

Many of these cultural treasures have suffered atmospheric and physical degradation over time. Many of the earliest images, taken before more robust techniques were developed,[1] are imperiled not only by their age, but by their fragility, which forbids the application of even the mildest physical and chemical conservation and restoration techniques.

The very sensitive surface microstructure of daguerreotypes, formed in silver and mercury surface particles is easily disrupted by atmospheric agents and can be damaged by the slightest physical contact. In many cases, the image is obscured

† ardis@cs.rochester.edu; Dept. of Comp. Science, Univ. of Rochester, P.O. Box 270226, 734 Comp. Studies Bldg., Rochester, NY 14627

by corrosion systems, extraneous deposits, or physical damage interrupting its ultra fine microstructure . In this way, the original images have lost critical visual information to dust particles, scratches, and chemical damage. Throughout the past century, numerous cleaning processes have been developed to restore parts of damaged daguerreotypes,[2–7] but current conservation research shows that even the gentlest of these processes can irreversibly alter the image or introduce potential for later damage. While researchers continue to develop conservation techniques, it is imperative that historically-important daguerreotypes be digitally imaged as soon as possible lest they suffer irreversible degradation in the meantime.

The nature and fragility of daguerreotypes not only means that they are constantly at risk of degradation, but that access to them must be limited, restricting their potential value to the public and the academic community. Digitized copies of these images, however, can be made available instantaneously through the Internet, and can serve as both a "virtual viewing room" and as a testing ground for new advances in simulated art conservation and the modeling of damage over time. Using these digital images, scientists may freely explore daguerreotype conservation techniques, safely providing insight into the preservation, conservation, and display of these images to the public at large.

We present the initial results of a collaboration between conservationists at the George Eastman House International Museum of Photography & Film and computer scientists at the University of Rochester: a full scan of the Cincinnati Waterfront Panorama Daguerreotype, an image owned by the Public Library of Cincinnati and Hamilton County, along with automatic tools for polishing-mark identification, dust detection, and image restoration. It is our intention to make this dataset (and accompanying algorithms) available for non-profit academic use; please contact `ardis@cs.rochester.edu` for details. It is our hope that other scientists will explore this massive dataset and develop techniques that go beyond the provided "baseline" curatorial tools, leading to the increased public availability of annotated and restored daguerreotypes.

The rest of this paper is structured as follows: Section 2 describes the construction of the *Cincinnati* dataset, Section 3 summarizes associated tools for automatic annotation, Section 4 outlines the use of Self-Similarity Inpainting[8] to provide an initial restoration, and Section 5 concludes.

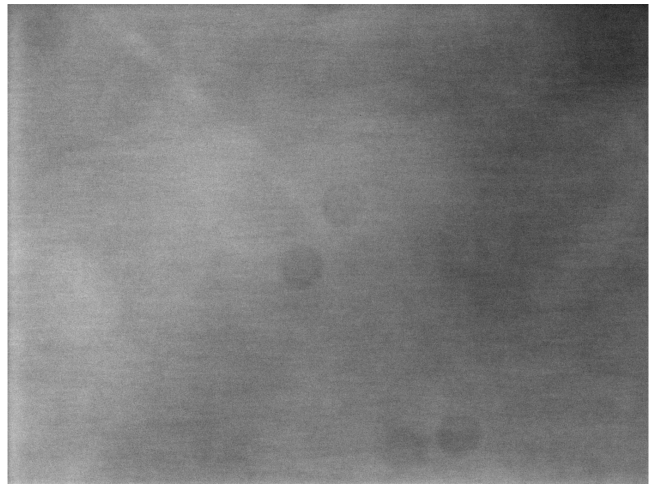
2. *CINCINNATI* DATASET

Conservation research staff at the George Eastman House have imaged the Cincinnati Waterfront Panorama Daguerreotype, also commonly known simply as "The Cincinnati Panorama" (Fig 1). Taken in September of 1848 and attributed to Charles Fontayne and William S. Porter*, the image consists of eight whole plate (6.5×8.5 inch) pieces with minor ($< 10\%$) overlap and provides a panoramic view of Cincinnati's waterfront. Imaged from Newport, KY, approximately five miles from the city center, this panorama captures minute details of the city's layout and construction (including seventeen boats identifiable by name and six historical landmarks), and has been compared with James Blakeway's Cincinnati panoramas of the 1990s (Fig. 2). A large-scale mural reproduction of the panorama may be found in the Atrium of the Public Library of Cincinnati and Hamilton County's South Building, with archival paper prints and postcards available for purchase through the library's website.

Imaging of each whole plate was performed at 16x magnification using a visible light to image fixed-size overlapping regions, for a total of 70,749,020,160 pixels (8 whole plates, each decomposed into 111×57 individually imaged regions of 1040×1344 pixels). At the time of writing, the entire dataset has been imaged, although annotation and restoration (Sections 3 and 4) has only been performed for one plate. Multiple diffused lights were positioned at approximately $15° - 25°$ from horizontal to avoid reflection or hot spots in the captured image, although the result was not uniform in intensity and resulted in gradiation that is noticeable in mosaic (Fig. 3(a)). This nonuniformity was compensated for, however, by using very large expert-identifed regions of uniform texture (*i.e.*, cloudless sky) and computing the average intensity image for each pixel across all of the uniform-textured 1040×1344 sub-images (Fig. 3(b)), thereby identifying spatial intensity bias that was then corrected prior to further processing. The entirety of the imaged result is included in the dataset that we are making available, hereafter referred to as the *Cincinnati* dataset, including automatic tools for annotation and restoration as described below.

*The makers' mark for this piece lists both daguerreians, although contemporary speculation is that Porter was the sole artist involved in this particular capture.

(a) Plate 4 (as mosaic of individually imaged portions)



(b) Average Image of Featureless Daguerreotype Regions

Fig. 3. Pre-correction Scan Results due to Nonuniform Lighting

3. ANNOTATION

Our work on automated daguerreotype annotation cover two very different observable phenomena: polishing scratches and embedded dust. While the latter is the result of imaging foreign particulates that are trapped in the oxygen-deprived housing of the physical daguerreotype,[9] the former refers to approximately parallel disturbances of the silver plate that are the result of polishing the plate with a regularly-textured material prior to image capture.[10,11] These different sources of image noise highlight both the variety of sources of degradation faced by daguerreotypes, and the extremely fine spatial detail that they offer.

3.1 Polishing Scratches

Polishing marks are roughly parallel due to the woven construction of the buffing materials used (*e.g.*, muslin, flannel). Weaving produces approximately periodic variation in the material, which then causes fine, similarly periodic micro-scratches of the plate as it is applied (Fig. 4(a)). While only visible at very high magnification, these marks prove highly informative: as particular daguerreotypists and daguerreotype studios have traditionally made use of particular polishing materials and procedures, producing uniquely-identifying patterns of scratches. As a result, a conservator trained in the study of these marks could potentially identify forgeries and hypothesize likely artists or photographers for pieces without provenance, using an image where scratches have been enhanced for visibility. Therefore, we provide a simple algorithm (Algorithm 1) for the automatic detection and enhancement of these scratches.

Algorithm 1: Baseline Enhancement of Polishing Scratches

Divide image $\mathcal{I}$ into n fixed-sized regions $\mathcal{I}_1, \mathcal{I}_2, \ldots, \mathcal{I}_n$;
for $i = 1$ **to** n **do**
- $A \leftarrow \mathrm{FFT}(\mathcal{I}_i)$; `// Convert to Fourier (frequency) domain`
- $B \leftarrow \mathrm{HPRF}(A)$; `// Isolate strong approximately periodic signals`
- $C \leftarrow \mathrm{IFFT}(B)$; `// Convert back to image domain`
- $D \leftarrow \mathrm{norm}(C \cdot \mathcal{I}_i)$; `// Multiply with original and renormalize`
- $\mathcal{I}_i \leftarrow D$; `// Store resulting (enhanced) image`

The functions and symbols used in the algorithm are defined as follows:

- $\mathrm{FFT}(\ldots)$ indicates the Fast Fourier Transform of the portion of the image under consideration (Fig. 4(b)).

- $\mathrm{HPRF}(\ldots)$ indicates a High Pass Radial Filter of the FFT image (Fig. 4(c)). That is, perform a logarithmic transformation of the FFT image, then zero out all rays whose average intensity (normalized within a fixed window of angle ψ) is below a threshold ρ. For the purposes of our initial experiments, $\rho = 20$ and the window size was $16°$.
- $\mathrm{IFFT}(\ldots)$ indicates the Inverse Fast Fourier Transform of the filtered FFT image (Fig. 4(d)).
- $\mathrm{norm}(\ldots)$ indicates the linear renormalization of the multiplied images to fit the original discretization (Fig. 4(e)).

This algorithm works because scratched portions of the silvered plate do not reflect as much light directly due to topical deformation, meaning that they appear as lines that are slightly darker than their surrounds. This enhancement process will "wash out" other textures, bringing the scratches into higher contrast for human viewing, and can be repeated (or otherwise magnified) as needed. While we have received reports that this process is helpful for trained conservation and curatorial staff, we do not yet have an objective measure of its effectiveness, and hope to eventually be able to experimentally validate and quantify it.

3.2 Dust

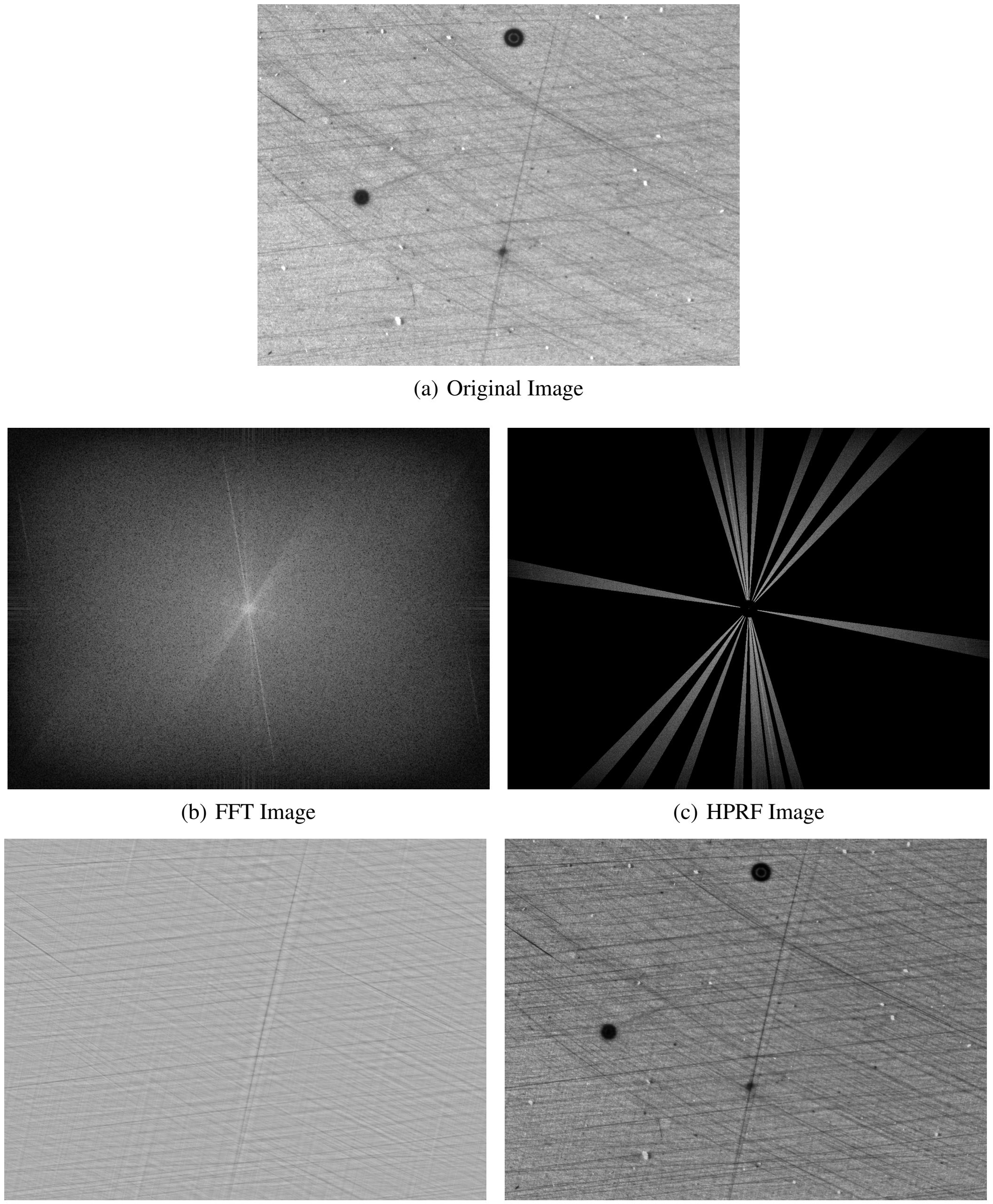
Unlike polishing scratches, which contain important information, dust primarily obscures image information and degrades daguerreotypes. Annotation of dust is therefore intended as a preliminary stage of image enhancement. Unfortunately, due to the massive size of the images, and the very small size of dust particles, it is an extraordinarily time-consuming process to manually identify portions of the imaged daguerreotype that correspond to obscuring dust. For instance, randomly sampled hand-labeled portions of the *Cincinnati* dataset contain dust at a rate of 0.2% (1 in every 500 pixels). This implies that our dataset contains approximately 140 million pixels corresponding to interfering particulates rather than the daguerreotype image. While the automatic detection of expert-identifiable damage is a well-studied task in image processing and computer vision,[12,13] such techniques have not yet become commonplace in the daguerreotype conservation community. This suggests a new set of challenging problems of unprecedented visual scale, where techniques are trained upon specialist-labeled data in the hopes of automatically annotating daguerreotypes for damage modeling, age and atmospheric analysis, and automatic restoration (Section 4).

Along with the *Cincinnati* dataset, we provide a baseline dust detector based upon the fast integration of semantically naïve low-level image features. Specifically, we apply Laplacian of Gaussians (LoG)[14] filters of two forms: traditional (where $LoG(x, y) = -\frac{1}{\pi\sigma^4}\left(1 - \frac{x^2+y^2}{2\sigma^2}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$ for constant σ) and simplified (where $LoG(x, y) = -1$ when $xy \neq 0$ and $LoG(0, 0) = \delta$ for positive constant δ). By varying the parameterization of these filters (*i.e.*, σ, δ), identifying when these break a constant threshold ψ, and feeding the results (along with a small amount of expert-labeled ground truth training data) into a kernel Support Vector Machine (SVM),[15,16] we are able to produce a composite detection system that outperforms any single filter and makes no prior assumptions about which parameterization will perform best.

This process is illustrated in Fig. 5: a portion of the dataset (Fig. 5(a)) is subjected to the (thresholded) convolution of each of the filters (Fig. 5(b)-5(d), etc.), and is supplied to an SVM along with a corresponding image that has been hand-labeled by experts (Fig. 5(e)), producing a composite classifier (Fig. 5(f)) intended for generalization to the entire dataset. For our initial experiments, we performed SVM training on 1% of the dataset, using 7 parameterized filters (4 traditional LoG, 3 simplified) and 3 different kernels (Radial Basis Function, Sigmoid, Inhomogeneous Polynomial) each of degree 3. Pixel label accuracies (compared to expert opinion, testing on 20% of reserved labeled data) are as follows:

- Average single-filter label accuracy: 99.811%
- Best single-filter label accuracy: 99.844%
- SVM [Radial Basis Function] label accuracy: 99.949%
- SVM [Sigmoid] label accuracy: 99.947%
- SVM [Inhomogeneous Polynomial] label accuracy: 99.949%

While all of these performance numbers may seem similar, these numbers reflect that thresholding a randomly parameterized filter produces inaccurate pixel labeling for 1 out of every 532 pixels, while thresholding an SVM-trained combination of filters reduces this to 1 out of every 1961. Although this improvement is dramatic, it still leaves approximately 4.5 million pixels per plate incorrectly labeled. Therefore, we challenge other authors to outperform our classifiers.



(a) Original Image

(b) FFT Image

(c) HPRF Image

(d) IFFT Image

(e) Final Image

Fig. 4. Automatic Scratch Enhancement

(a) Original Image

(b) First Detector Results (red)

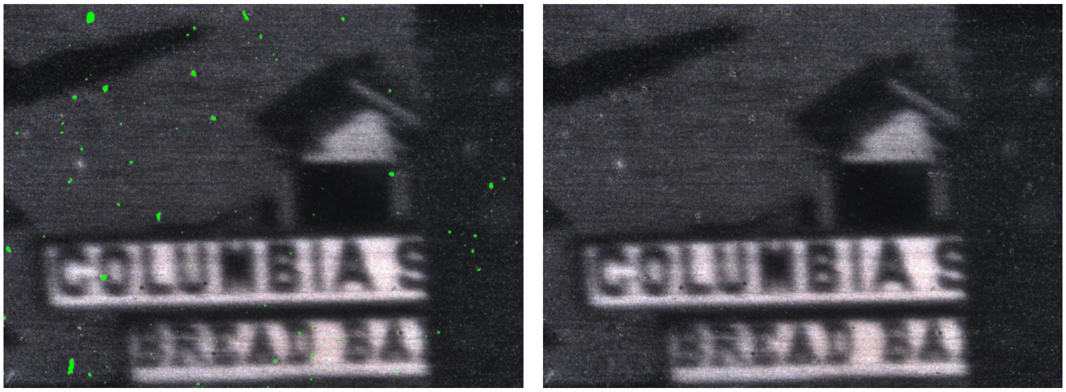
(c) Second Detector Results (red)

(d) Third Detector Results (red)

(e) Hand-Labeled Data (green)

(f) SVM-based Detector Results (blue)

Fig. 5. SVM-based Dust Detection and Annotation



(a) Image Portion (prior to restoration) (b) Restored Image Portion

Fig. 6. Automatic Restoration through Self-Similarity Inpainting

4. RESTORATION

Beyond finding damaged parts of images, there is a corresponding interest in repairing that damage. Because of the fragile and non-reproducible nature of daguerreotypes, digital restoration is an attractive alternative to risky chemical and physical restorative techniques. While future work is planned that incorporates a more complex model of image formulation[17] and (in-process) observations of artificial atmospheric daguerreotype aging, we provide here our initial results in removing the obscuring dust from Section 3.2 (Fig. 6(a)). We chose to restore all pixels corresponding to identified dust as well as nearby pixels forming the smallest tight-fitting rectangle of 3×3 squares.

Given the non-uniform, grainy texture of the daguerreotype under high magnification, we chose to restore it using Self-Similarity Inpainting,[8] a technique that emphasizes textural continuity. Self-Similarity Inpainting involves the insertion of textured patches (in this case, 3×3 pixels) from an undamaged part of the image. This technique selects the patch to insert based upon the similarity of the surroundings of the patch before and after copying. That is, a measure of local "self-similarity"[18] is computed for each fixed-sized window, then compared with the resulting measure when (hypothetically) inserted to fill-in missing data. In order to perform this operation quickly for the entire dataset, and take advantage of this dataset's huge image sizes, we truncated the search for potential patches from the entirety of the image (which would be intractable for the entire plate) to a 15×15 window around the hole. Results of this "windowed" application of Self-Similarity Inpainting to a particularly challenging segment (of inhomogeneous texture) are shown in Fig. 6(b).

5. CONCLUSIONS

We have introduced an important new dataset of images of unprecedented visual scale. While we have presented a set of baseline techniques for annotating and restoring these images, it is our hope that authors take up the challenge of the *Cincinnati* dataset and pursue automatic daguerreotype annotation and restoration; interested parties should contact `ardis@cs.rochester.edu`. In this way, such massive (gigapixel) images serve as more than archives of degrading historical artifacts, but also act as interesting targets for contemporary image processing and computer vision techniques aimed at image enhancement, understanding, and correction.

REFERENCES

[1] Lerebours, N. P., [*A Treatise on Photography; containing the Latest Discoveries and Improvements Appertaining to the Daguerreotype*], Longman, Brown, Green, and Longmans (1843). Translated by J. Egerton.

[2] Daniels, V., "Plasma reduction of silver tarnish on daguerreotypes," *Studies in Conservation* **26**(2), 45–49 (1981).

[3] Barger, M. S., Krishnaswamy, S. V., and Messier, R., "The cleaning of daguerreotypes: Comparison of cleaning methods," *Journal of the American Institute for Conservation* **22**(1), 13–24 (1982).

[4] Irvine, R. F., "Care and cleaning of the non-contemporary photographic image," *Journal of Visual Communication in Medicine* **13**(2), 61–63 (1990).

[5] Turovets, I., Maggen, M., and Lewis, A., "Cleaning of daguerreotypes with an excimer laser," *Studies in Conservation* **43**(2), 89–100 (1998).

[6] Golovlev, V. V., Gresalfi, M. J., Miller, J. C., Romer, G., and Messier, P., "Laser characterization and cleaning of 19th century daguerreotypes," *Journal of Cultural Heritage* **1**(1), 139–144 (2000).

[7] Golovlev, V. V., Gresalfi, M. J., Miller, J. C., Anglos, D., Melesanaki, K., Zafiropulos, V., Romer, G., and Messier, P., "Laser characterization and cleaning of 19th century daguerreotypes ii," *Journal of Cultural Heritage* **4**(1), 134–139 (2003).

[8] Ardis, P. A. and Brown, C. M., "Self-similarity inpainting," in [*Proceedings of the 2009 IEEE International Conference on Image Processing*], (2009).

[9] Barger, M. S., Messier, R., and White, W. B., "Gilding and sealing daguerreotypes," *Photographic Science and Engineering* **27**(4), 141–146 (1983).

[10] Humphrey, S. D., [*American Handbook of the Daguerreotype*], S. D. Humphrey (1858).

[11] Draper, J. W., "On the process of daguerreotype, and its application to taking portraits from the life," *Philosophical Magazine Series 3* **17**(109), 217–225 (1840).

[12] Kokaram, A. C., Morris, R. D., Fitzgerald, W. J., and Rayner, P. J. W., "Detection of missing data in image sequences," *IEEE Transactions on Image Processing* **4**(11), 1496–1508 (1995).

[13] Joyeux, L., Bulsson, O., Besserer, B., and Boukir, S., "Detection and removal of line scratches in motion picture films," in [*Proceedings of the 1999 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*], **1**, 1548–1554 (1999).

[14] Marr, D., [*Vision: a Computational Investigation into the Human Representation and Processing of Visual Information*], Henry Holt and Co., Inc. (1982).

[15] Cortes, C. and Vapnik, V., "Support vector networks," *Machine Learning* **20**(3), 273–297 (1993).

[16] Chang, C.-C. and Lin, C.-J., *LIBSVM: a library for support vector machines* (2001). Software available at http://www.csie.ntu.edu.tw/ cjlin/libsvm.

[17] Barger, M. S., Messier, R., and White, W. B., "A physical model for the daguerreotype," *Photographic Science and Engineering* **26**(6), 285–291 (1982).

[18] Shechtman, E. and Irani, M., "Matching local self-similarities across images and videos," in [*Proceedings of the 2007 IEEE Conference on Computer Vision and Pattern Recognition*], 1–8 (2007).