

# An Exemplar-Based Method for Automatic Visual Editing and Retouching of Fine Art Reproduction

Jun Jiang and Jinwei Gu. *Munsell Color Science Laboratory, Center for Imaging Science, Rochester Institute of Technology, Rochester, NY, USA*

## Abstract

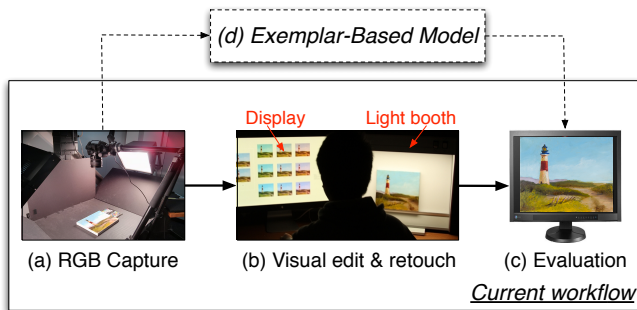
The advance in camera and imaging technologies has made digital archiving and conservation of artworks possible in museums. Visual editing and retouching are usually made by experts in museums to match the reproduction with the original more closely. While effective, visual editing and retouching is time-consuming and labor-intensive. We addressed this problem by learning from the adjustments made by observers, and automatically making visual editing and retouching on incoming paintings. The evaluation results suggest that the image adjusted by our model is significantly better than the average of the images adjusted by observers.

## Introduction

The digital archiving of fine art paintings in museums enables both easy access and better preservation of artworks. To achieve this aim, most museums involve *visual editing* and *retouching*<sup>1</sup> to match the reproduction with the original more closely [2]. The process of visual editing and retouching can be tedious and subjective. In this paper, we tried solving this problem by machine learning techniques.



**Figure 2.** Painting acquisition. Canon 60D is mounted perpendicular to the painting on the stage. Two diffuse studio lightings are put on both sides at 45° from the stage. ColorChecker is used to correct image white balance after capturing.



**Figure 1.** A general workflow of fine art reproduction in museums. (a) A painting is captured by a digital camera under a certain lighting geometry. (b) Visual editing and retouching are made by experts on the reproduction to match with the original in the CIE D50 light booth. In the paper, we propose an exemplar-based method (d) to model the process of visual editing and retouching to yield results that are similar in image quality with those adjusted by observers.

The main components in current workflows of fine art reproduction are in Fig. 1. The painting is captured by a camera under a certain lighting geometry. Despite using high-end cameras and

<sup>1</sup>Visual editing refers to the global adjustments, and retouching refers to local and sharpness adjustments of a captured image to match with the original painting [1].

studio lightings, the reproductions off the camera usually do not match with the original because (1) the camera spectral sensitivity does not approximate human color matching functions very well (Luther condition [3, 4]), (2) the improper lighting geometry could flatten the texture or cause unwanted shadows, and (3) some of the colors in the painting may be beyond the device gamut.

To address the mismatch in color, experts tend to make visual editing and retouching on the reproduction off the camera. While color accuracy is improved after visual editing, Berns and Frey [2] found visual editing and retouching time-consuming.

It is therefore of great interest to automate visual editing, at the same time providing satisfying results on par with the adjusted images by experts, as labeled as *Exemplar-Based Model* in Fig. 1. With this goal, our contributions in this paper are as follows:

- We proposed an end-to-end pipeline to digital archive artworks without manual visual editing.
- We derived a distance metric similar to [5] to relate visual editing and retouching by observers with the image difference between paintings.
- Given a new painting, we find the painting in the database that matches with the new painting most closely, and apply global and local adjustments based on the best-matched painting.
- We evaluated our model by comparing with images adjusted by observers in a paired-comparison study.

The distance metric to find the best match between the new image and an existing image in the database is similar to [5]. However, our paper is different in three aspects:

- We propose to improve the reproduction accuracy from the original. Most previous work focus on enhancing the image quality by making pleasing pictures. The data collected in our project is more relevant for museum applications, where accuracy is of top priority.
- Not only global adjustments, but local tunings are also learnt in our model. Recently Hwang et al. [6] enhanced images with local adjustments based on texture. Instead, our approach is color oriented.
- In [5], the adjustment parameters of training images are obtained by an auto-enhancement module. However, our training data are from real observers.

## Related Work

**Visual Editing and Retouching** Visual editing and retouching refers to the global and local adjustments by experts on reproductions off the camera to match with the original. It is one of the most difficult part to automate and standardize in the workflow of fine art reproduction. Jiang et al. [7] proposed to find a closer starting point for visual editing by using more perceptually advanced chromatic adaptation transform (CAT). Berns et al. [8], Miyake et al. [9], and Hardeberg et al. [10] used imaging systems composed of color filters or liquid crystal tunable filters (LCTFs) to reproduce the painting spectra. By estimating the spectra of the painting, the reproduction and the original are more likely to match in color under different lighting [11]. Nevertheless, the introduction of spectral imaging in museums may require an investment on both equipment and technology, and a big change in the workflow.

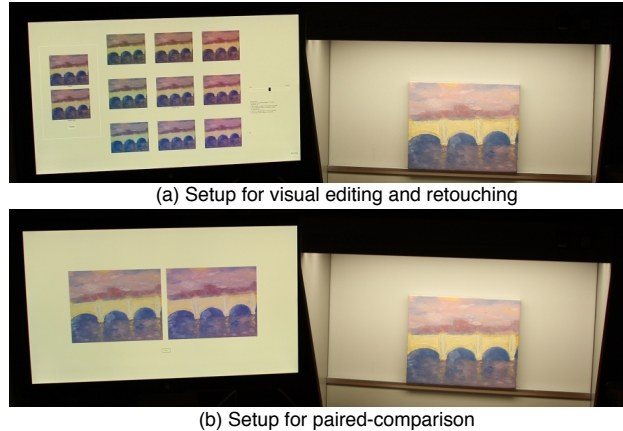
On the other hand, our exemplar-based method works with current camera and lighting setups, and the results by the model is found significantly better than the average of the images after visual editing by observers.

**Exemplar-Based Model** Image adjustments are usually made to improve the image quality by changing image tint, sharpness and so on. An exemplar-based method has been found effective in enhancing the images. It includes, in a more general sense, colorization of a gray image [12, 13, 14], tone and texture transferring [15]. Dale et al. [16] restored the image using an online photo database. Kang et al. [5] proposed to enhance the image by incorporating user preference through learning image adjustments on photo collections. Hwang et al. [6] made local image enhancement by first looking for images in a training database that are closest to the new image. Joze and Drew [17] addressed the problem of color constancy by searching for matched images in a database whose illuminant is known.

In our paper, we focus on improving image *accuracy* rather than making pleasing images by an exemplar-based approach.

## Gathering Training Data of Visual Editing and Retouching

In the paper, we propose to automate the process of visual editing and retouching by a model learnt from the adjustments on the paintings by observers. The training data were collected by



**Figure 4.** The setup for the psychophysics experiment. (a) The setup for visual editing and retouching. Observers were asked to adjust the image on the display to match with the original in the light booth. (b) The setup for the paired-comparison experiment. Observers were asked to choose the image on the display that matches with the original in the light booth more closely.

having observers make visual editing and retouching on our captured paintings. In the remainder of this paper, Section shows how we photographed the paintings, Section shows the visual editing and retouching by observers on our user interface, Section shows the details of the automatic adjustment algorithms learned from the training data, and Section is the evaluation of our model, which shows our method is better than the average of images after visual editing by observers.

## Painting Acquisition

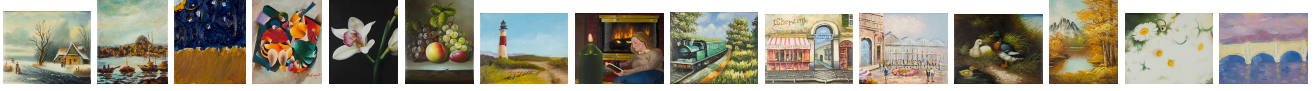
The artworks are oil paintings (8x10 inches), Fig. 3, and they were digitized by Canon 60D. SoftCube studio lightings are used with little heat generated to avoid harming the paintings, Fig. 2. Lights are put on both sides at 45° from the horizontal stage to provide diffuse light on the painting without causing shadows.

## Psychophysics Experiments

Twenty-five observers participated in our experiment, most of whom are college students. Each observer is asked to adjust five of all fifteen paintings, and it takes about an hour for one observer to finish the experiment. Observers were asked to adjust the softcopy on the display to match with the original in the CIE D50 light booth, Fig. 4 (a).

A 27-inch Apple Cinema Display was used for showing reproductions. It was characterized using an LMT 1210 colorimeter to ensure color accuracy [18]. Display white point and luminance were adjusted to match with those of the light booth by using a Halon perfect reflecting diffuser (PRD). Additionally, the luminance and chromaticity of the background of the light booth were measured using a PhotoReserach-650 spectroradiometer. The background of the software interface was adjusted to match these settings.

The pipeline and user interface for the experiment are similar to [7] in Fig. 5. Upon capturing of the painting, white balance was adjusted in Photoshop with the aid of the ColorChecker in the scene. The linear Bradford chromatic adaptation transform (CAT) is used to convert the captured images from AdobeRGB



**Figure 3.** Paintings that are used in the experiment. The last five are used in the evaluation of the model in Fig. 9 and Table. 1.

color space (default white point: CIE D65) to the display white point (CIE D50) before images are shown on the display.

Visual editing and retouching are highlighted in the dashed-line rectangle in Fig. 5 (a). Image hue is adjusted by selecting one of the surrounding images at different hue angles around the *current pick* in the center in Fig. 5 (b). Image lightness and chroma are adjusted by a power function by Eq. 1 and in Fig. 6 (a).

$$\mathbf{I}_{\text{out}} = \mathbf{I}_{\text{in}}^\gamma, \quad (1)$$

where  $\mathbf{I}_{\text{in}}$  and  $\mathbf{I}_{\text{out}}$  are the images normalized between 0 and 1 before and after the adjustment, and  $\gamma$  is the parameter to change the property of the image. Image hue is adjusted similarly by Eq. 1 on  $a^*$  and  $b^*$  in CIELAB [19]. Contrast is adjusted on the lightness alone by Eq. 2 and in Fig. 6 (b).

$$\mathbf{I}_{\text{out}} = \begin{cases} \frac{(\mathbf{I}_{\text{in}} - 2)^\alpha}{2}, & \text{if } \mathbf{I}_{\text{in}} < 0.5, \\ 1 - \frac{((1 - \mathbf{I}_{\text{in}}) - 2)^\alpha}{2}, & \text{if } \mathbf{I}_{\text{in}} \geq 0.5, \end{cases} \quad (2)$$

where  $\alpha$  is to adjust image contrast.

Local adjustments are made in Fig. 5 (d) based on Eq. 1 and 2. Instead of making changes to the whole image, local adjustments are applied to certain colors in the image. Sharpness adjustment is achieved by unsharp mask [20] in Fig. 5 (e). The parameter for each user adjustment is saved to train the model.

## Automatic Visual Editing and Retouching

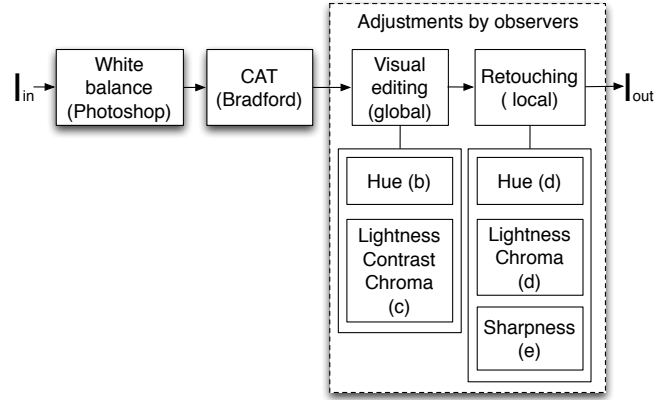
A distance metric similar to [5] is learnt to relate image difference with the difference in the space of image adjustments. With a new image, its image difference from all the images in the database is calculated, based on which the best-matched image in the database is found. Global adjustments (Section ) of the best-matched image is applied to the incoming painting.

Local adjustments (Section: ) are performed if the dominant colors (and their neighboring colors) in the new painting match with those in the best-matched painting.

### Global Adjustments

In order to make proper global adjustments to a new painting, a distance metric is defined in order to find an existing painting in the database that is closest to the new painting. The distance metric is learnt by mapping the image difference between all pairs of paintings in the database, and the difference in the adjustment parameters by observers, as shown in Eq. 3,

$$\begin{aligned} & \begin{bmatrix} d_1(I_1, I_2), & d_2(I_1, I_2), & \dots & d_m(I_1, I_2) \\ d_1(I_1, I_3), & d_2(I_1, I_3), & \dots & d_m(I_1, I_3) \\ \dots & \dots & \dots & \dots \\ d_1(I_{n-1}, I_n), & d_2(I_{n-1}, I_n), & \dots & d_m(I_{n-1}, I_n) \end{bmatrix} \cdot \mathbf{T} \\ &= \begin{bmatrix} \sum_1^K (C_{1,k} - C_{2,k})^2 \\ \sum_1^K (C_{1,k} - C_{3,k})^2 \\ \dots \\ \sum_1^K (C_{n-1,k} - C_{n,k})^2 \end{bmatrix}, \quad (3) \end{aligned}$$



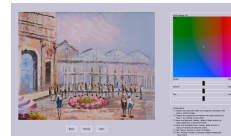
(a) Pipeline of image adjustments



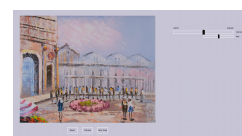
(b) Hue



(c) Global

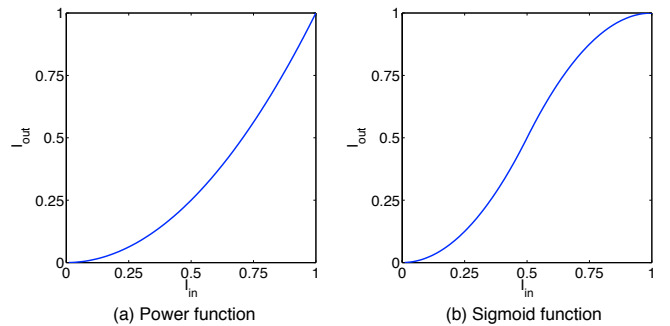


(d) Local



(e) Sharpness

**Figure 5.** The pipeline to make visual editing and retouching of the captured images. The components in the dashed-line rectangle in (a) correspond to the adjustments by observers. User interfaces: (b) hue, (c) global, (d) local, and (e) sharpness.



**Figure 6.** (a) The power function to adjust the image lightness, chroma and hue, and (b) the sigmoid function to adjust contrast.

where  $n$  is the number of paintings, and  $m$  is the number of image distance metrics.  $d_m(I_{n-1}, I_n)$  is the  $m$ th image difference metric between the  $(n-1)$ th and  $n$ th image. The image difference metrics are generally L-2 and L-1 norm of the difference between two images in certain space (CIELAB [19], *e.g.*). Some of the image difference used in our calculations are *RMS* (root mean square),  $1/SSIM$  [21], and  $\Delta E_{00}$  [22].  $C_{n,k}$  is the  $k$ th adjustment parameter for the  $n$ th painting. In our experiment, observers are able to adjust the overall image hue, contrast, lightness, chroma, and sharpness, thus  $K$  being 6 as shown in Eq. 4,

$$\mathbf{C} = (\gamma_{a^*}, \gamma_{b^*}, \gamma_{L^*}, \gamma_{C_{ab}^*}, \alpha, s), \quad (4)$$

where  $\gamma_{a^*}$  and  $\gamma_{b^*}$  are used to adjust the image hue by Eq. 1,  $\gamma_{L^*}$  and  $\gamma_{C_{ab}^*}$  are to change image lightness and chroma by Eq. 1,  $\alpha$  is for contrast adjustment by Eq. 2, and  $s$  is for sharpness adjustment using unsharp mask [20].

The matrix form of Eq. 3 can be written as  $\Delta \mathbf{D} \cdot \mathbf{T} = \Delta \mathbf{C}$ , where  $\Delta \mathbf{D}$  is a  $(n-1)$ -by- $m$  image difference matrix,  $\Delta \mathbf{C}$  is a  $(n-1)$ -by-1 vector representing the difference in the space of adjustment parameters, and  $\mathbf{T}$  is a  $m$ -by-1 vector. Given the adjustments by observers on the paintings, and the image difference,  $\mathbf{T}$  can be calculated by Eq. 5,

$$\mathbf{T} = \Delta \mathbf{D}^+ \cdot \Delta \mathbf{C}. \quad (5)$$

When a new painting arrives, its difference with all the paintings in the database is calculated, and its distance from other paintings in the space of adjustment parameters can be obtained by Eq. 6,

$$\Delta \mathbf{C}_{new} = \Delta \mathbf{D}_{new} \cdot \mathbf{T}. \quad (6)$$

where  $\Delta \mathbf{D}_{new}$  is a  $n$ -by- $m$  matrix of image difference between the new image and all the images in the database, and  $\Delta \mathbf{C}_{new}$  ( $n$ -by-1) is the distance in the space of adjustment parameters between the new painting and those in the database. The painting with the smallest value in  $\Delta \mathbf{C}_{new}$  in Eq. 6 is matched to the new painting. Global adjustment is made by Eq. 7,

$$\mathbf{I}_{afterGlobal} = f_{global}(\mathbf{I}, \mathbf{C}_i), \quad \Delta C_i = \min(\Delta \mathbf{C}_{new}), \quad (7)$$

where  $\mathbf{I}$  and  $\mathbf{I}_{afterGlobal}$  is the image before and after the adjustment,  $f_{global}$ .  $\mathbf{C}_i$  is the global adjustment parameters of the  $i$ th image, whose  $\Delta C_i$  is the smallest in  $\Delta \mathbf{C}_{new}$ .

### Local Adjustments

When the overall color of the painting is adjusted, local adjustments are made to certain colors to match with the original more closely. The adjustment parameters for the local adjustments include hue, lightness, chroma, and threshold by Eq. 8,

$$\mathbf{C} = (LCH, h, \gamma_{L^*}, \gamma_{C_{ab}^*}, t), \quad (8)$$

where  $LCH$  is the selected color for adjustment in the CIE LCH [19],  $h$  is the target hue,  $\gamma_{L^*}$  and  $\gamma_{C_{ab}^*}$  are for lightness and chroma adjustment by Eq. 1,  $t$  is the threshold to determine the range of color from the selected color,  $LCH$ , as a centroid, to be adjusted.

Local adjustments are shown in Fig. 7. Dominant colors are extracted from the new painting by K-means clustering [23] in CIELAB [19]. To avoid dominant colors that are very close in color are selected, threshold is set to group colors that are within a certain color tolerance.

After identifying the dominant colors, their neighboring colors are examined, Fig. 7. The selected colors in the best-matched painting and their neighboring colors are compared with those in the new painting. Local adjustments are made if a dominant color matches with a selected color, and so do their corresponding neighboring colors.

The global, local and sharpness adjustment of *Firelight* is in Fig. 8. Multidimensional scaling (MDS) is used to understand the contribution of each step based on color difference. The blue dots are the reproductions adjusted by observers. It is expected that our model (red dots) should move closer to the images adjusted by observers, thus being able to replace visual editing by observers.

Most changes in *Firelight* are from global adjustments, Fig. 8 (e). This may result from local adjustment affecting only certain colors in the image, making it hardly perceivable when mean color difference across the image is used as distance for MDS. Similarly, the perception of sharpness may not be well correlated with color difference.

### Evaluation of Automatic Visual Editing and Retouching

To evaluate our model, the images adjusted by our model were compared with those adjusted by observers in a paired-comparison experiment.

Given the available paintings (fifteen in total), one painting was used for validation while the rest for training  $\mathbf{T}$  in Eq. 5. The process is repeated for the last five paintings in Fig. 3. During evaluation, we ask observers to pick the image that matches the original more closely, Fig. 4 (b).

To get the rank of the painting, the probability of one painting that is selected over another is calculated by Eq. 9.

$$p(i, j) = \frac{n(i, j)}{n}, \quad (9)$$

where  $n(i, j)$  is the number of times that the  $i$ th image is chosen to be closer to the original than the  $j$ th image, and  $n$  is the total number of comparisons. The probability is then converted to zscore by Eq. 10.

$$x = F^{-1}(p|\mu, \sigma), \quad \mu = 0 \text{ and } \sigma = 1. \quad (10)$$

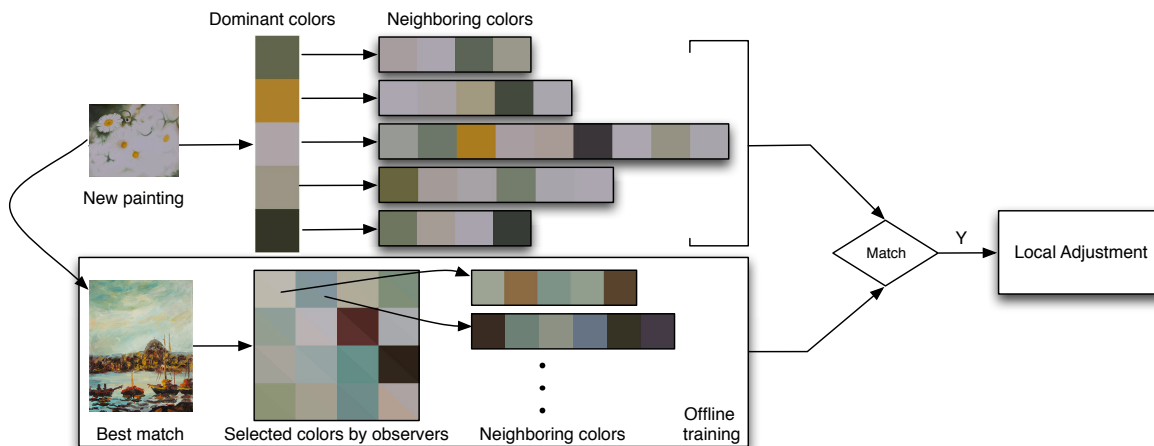
where  $p = F(x|0, 1) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{t^2}{2}} dt$ .

Ten observers evaluated the painting *Fall*, and fourteen observers evaluated the other four paintings. Overall our model is ranked higher than the average of the images adjusted by observers, Fig. 9.

Hypothesis test is used to tell whether the image adjusted by the model is significantly better than the average of images adjusted by observers (of the same painting). The null and alternative hypothesis thus become  $H_0 : \pi = 1/2$ , and  $H_\alpha : \pi > 1/2$ . With enough observers (repetitions) and adjusted images by observers (treatments), the normal approximation can be used to test the significance by Eq. 11 [25],

$$X = Z \cdot \sqrt{n(t-1)pq} + n(t-1)p + \frac{1}{2}, \quad (11)$$





**Figure 7.** The workflow for local adjustments. The new painting, Daisy is matched to Boats (Best match). Local adjustments are made by comparing the dominant color and their neighboring colors of Daisy with those of Boats. In the Selected colors by observers, below and above the diagonal within each patch is the color before and after local adjustments.

**Statistical test of model performance.** If the actual number is greater than  $X$ , the adjusted image by the model is significantly better than the average of the images adjusted by observers. The paintings for evaluation are the last five in Fig. 3.

	$X$ in Eq. 12	actual number	significant ( $\alpha = 0.05$ )
Plaza	42	48	Y
Ducks	50	51	Y
Fall	37	40	Y
Daisy	58	69	Y
Bridge	66	74	Y

where  $X$  is the number of times that the image by our model is selected in order to reject the null hypothesis.  $Z$  is  $1.645^2$ ,  $n$  is the number of observers,  $t$  is the number of stimuli (images) for paired-comparison,  $p = 1/2$ , and  $q = 1 - p$ . Eq 11 becomes

$$X = 1.645 \cdot \sqrt{\frac{n(t-1)}{4}} + \frac{n(t-1)}{2} + \frac{1}{2}. \quad (12)$$

If the actual number of times that the image by our model is selected by observers is greater than  $X$  in Eq. 12,  $H_0$  is rejected, suggesting our model is significantly better than the average. The result is summarized in Table. 1. The actual number of times that our model being selected is greater than  $X$  for all five paintings. Therefore the null hypothesis is rejected, indicating the images adjusted by our model is at least better than those adjusted by observers on average.

## Discussions

In this work, we model visual editing and retouching by an exemplar-based approach. A complete pipeline including capturing of the artwork, training of the model, adjustments of paintings,

<sup>2</sup> $Z$  is calculated based on type I error,  $\alpha = 0.05$ . 5% chance to reject the null hypothesis even when it is true.

and evaluation of the model is presented. The statistical analysis suggests that our model provides results that are at least better than the average of the visual editing and retouching by observers.

The performance of the model relies on the number and variety of paintings in the database that have been adjusted by observers. By adding more training images to the database, the performance of the model is likely to be improved. Compared with the tedious process of visual editing and retouching each single painting, our model provides an accurate and efficient solution.

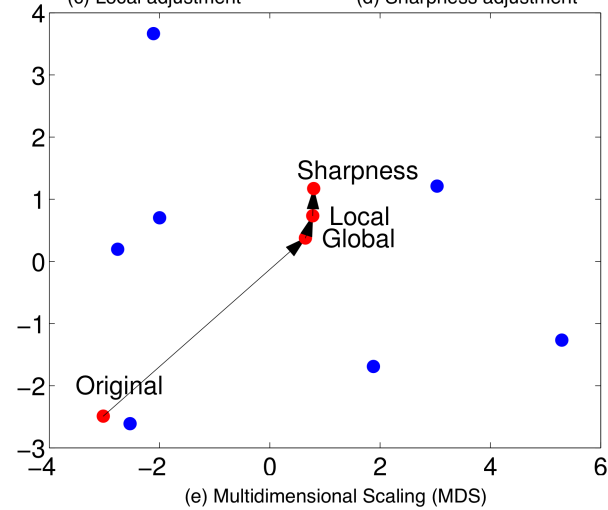
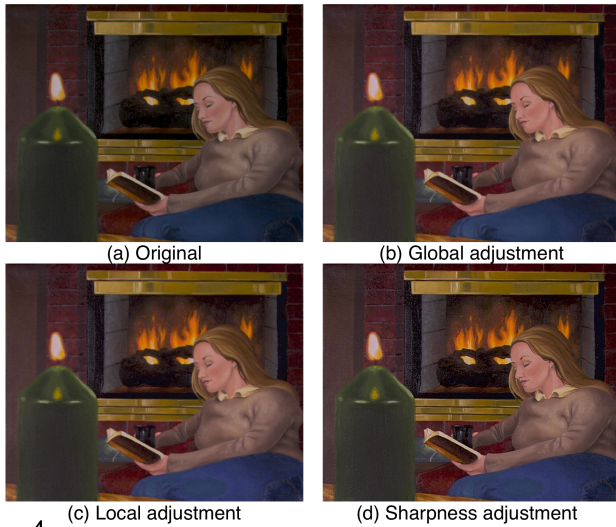
One of the limitations of our model is that the auto-adjustments can only be made to images that are acquired under the same settings as training images. Once lighting or camera setting is changed, the model has to be re-trained. While the workflows for fine art reproduction are widely varying across museums, the camera and lighting configurations within a museum are usually fixed. Our model may still be useful in the digital archiving of artworks in museums where the capturing setup is relatively stable.

## Conclusions

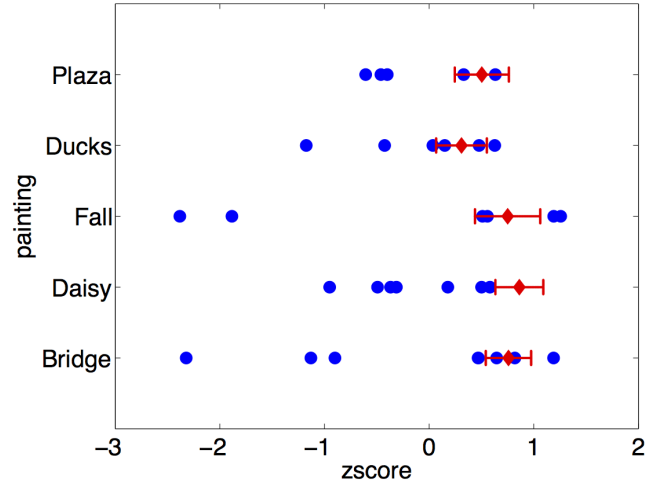
In the project, we use exemplar-based techniques to model visual editing and retouching by observers, based on which new paintings can be auto-adjusted. Statistical analysis suggests that the adjusted image by our model is more faithful to the original than the average of those adjusted by observers.

## References

- [1] Mitchell R Rosen and Franziska S Frey. RIT American museums survey on digital imaging for direct capture of artwork. In *Proceedings. IS&T Archiving Conference (Society for Imaging Science and Technology, Springfield, Va., 2005)*, (to be published), 2005. 1
- [2] Roy S Berns and Franziska S Frey. *Direct Digital Capture of Cultural Heritage: Benchmarking American Museum Practices and Defining Future Needs*. Rochester Institute of Technology, 2005. 1
- [3] Junichi Nakamura. *Image Sensors and Signal Processing for Digital Still Cameras*. CRC Press, 2006. 1



**Figure 8.** The adjustment results of Firelight at each step: (a) the original, (b) after global adjustments, (c) after local adjustments, and (d) after sharpness adjustment. Multidimensional scaling (MDS) is used to understand the contribution of each step based on color difference. The blue dots are the reproductions adjusted by observers, and the red dots are adjustments by our model at each step. Most of the changes in Firelight can be explained by the global adjustments.



**Figure 9.** The paired-comparison results for the five paintings. (Ten observers evaluated the painting Fall, and fourteen observers evaluated the other four paintings.) The blue dots are images adjusted by observers, and the red diamonds are the images predicted by our model. The greater the zscore, the more faithful the reproduction is to the original. Overall our model is ranked higher than the average of the images adjusted by observers. The paintings on the y-axis are the last five images in Fig. 3. Red bars are the 95% confidence intervals [24].

- [4] Jun Jiang, Dengyu Liu, Jinwei Gu, and Sabine Susstrunk. What is the space of spectral sensitivity functions for digital color cameras? *Workshop on the Applications of Computer Vision (WACV)*, 2013. 1
- [5] Sing Bing Kang, Ashish Kapoor, and Dani Lischinski. Personalization of image enhancement. In *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, pages 1799–1806. IEEE, 2010. 1, 2, 3
- [6] Sung Ju Hwang, Ashish Kapoor, and Sing Bing Kang. Context-based automatic local image enhancement. In *Computer Vision—ECCV 2012*, pages 569–582. Springer, 2012. 2
- [7] Jun Jiang, Franziska Frey, and Susan Farnand. Evaluating cats as predictors of observer adjustments in softcopy fine art reproduction. *Eighteenth Color and Imaging Conference*, pages 54–61, 2010. 2
- [8] Roy S. Berns, Lawrence A. Taplin, Mahdi Nezamabadi, Mahnaz Mohammadi, and Yonghui Zhao. Spectral imaging using a commercial color-filter array digital camera. In *14th Triennial ICOM-CC meeting*, pages 743–750, September 2005. 2
- [9] Yoichi Miyake, Yasuaki Yokoyama, Norimichi Tsumura, Hideaki Haneishi, K Miyata, and Junichiro Hayashi. Development of multi-band color imaging systems for recording of art paintings. In *Proc. SPIE*, volume 3648, pages 218–225, 1999. 2
- [10] Jon Y. Hardeberg, Francis Schmitt, and Hans Brettel. Multispectral image capture using a tunable filter. *Optical Engineering*, 41:2532–2548, 2008. 2
- [11] Roy S. Berns, Lawrence A. Taplin, Mahdi Nezamabadi, Yonghui Zhao, and Yoshio Okumura. High-accuracy digital imaging of cultural heritage without visual editing. In *IS&T's 2005 Archiving Conference*, pages 91–95, 2005. 2

- [12] Tomihisa Welsh, Michael Ashikhmin, and Klaus Mueller. Transferring color to greyscale images. *ACM Transactions on Graphics*, 21(3):277–280, 2002. 2
- [13] Youngha Chang, Keiji Uchikawa, and Suguru Saito. Example-based color stylization based on categorical perception. In *Proceedings of the 1st Symposium on Applied perception in graphics and visualization*, pages 91–98. ACM, 2004. 2
- [14] Baoyuan Wang, Yizhou Yu, and Ying-Qing Xu. Example-based image color and tone style enhancement. *ACM TOG*, 30:4, 2011. 2
- [15] Erik Reinhard. Example-based image manipulation. *Sixth European Conference on Colour in Graphics, Imaging, and Vision (CGIV)*, pages 1–4, 2012. 2
- [16] Kevin Dale, Micah K Johnson, Kalyan Sunkavalli, Wojciech Matusik, and Hanspeter Pfister. Image restoration using online photo collections. In *Computer Vision, 2009 IEEE 12th International Conference on*, pages 2217–2224. IEEE, 2009. 2
- [17] Hamid Reza Vaezi Joze and Mark S. Drew. Exemplar-based colour constancy. *British Machine Vision Conference*, September 2012. 2
- [18] Ellen A. Day, Lawrence Taplin, and Roy S. Berns. Colorimetric characterization of a computer-controlled liquid crystal display. *Color Research and Application*, 29:365–373, 2004. 2
- [19] Roy S. Berns. *Billmeyer and Saltzmanns Principles of Color Technology*. A Wiley-Interscience Publication, 2000. 3, 4
- [20] Rafael C Gonzalez, Richard E Woods, and Steven L Eddins. *Digital image processing using MATLAB*, volume 2. Gatesmark Publishing Tennessee, 2009. 3, 4
- [21] Zhou Wang, Alan C Bovik, Hamid Rahim Sheikh, and Eero P Simoncelli. Image quality assessment: From error visibility to structural similarity. *Image Processing, IEEE Transactions on*, 13(4): 600–612, 2004. 4
- [22] M. R. Luo, G. Cui, and B. Rigg. The development of the CIE 2000 colour-difference formula:CIEDE2000. *Color Research and Application*, 26:341–450, 2000. 4
- [23] George AF Seber. *Multivariate observations*, volume 252. Wiley, 2009. 4
- [24] Ethan D Montag. Empirical formula for creating error bars for the method of paired comparison. *Journal of Electronic Imaging*, 15(1): 010502–010502, 2006. 6
- [25] TH Starks and HA David. Significance tests for paired-comparison experiments. *Biometrika*, 48(1/2):95–108, 1961. 4