A Preliminary Study of Multi-Spectral Image Capturing for Oriental Water Color Painting

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Abstract

This study uses both multi-spectral and tri-chromatic approaches to capture Oriental water color painting with a digital camera. A Macbeth ColorChecker (24 colors) is used as the training target for both approaches. The multi-spectral approach uses a multi-illumination configuration to generate 6-channel signals. A pseudo inverse method is used to derive the transformation matrix and then to estimate the reflectances of the tested Oriental water color patches. The tri-chromatic approach uses a polynomial method to characterize the camera and then colorimetrically estimates the tested Oriental water color patches accordingly.

Six commonly used colors in Oriental water color have been chosen and four shades of each color have been used. These 24 color patches are used as the painted targets. When including the painted targets in the training data, the multi-spectral approach performs better than the tri-chromatic approach by generating fewer average colorimetric errors in reproducing the painted targets. Without the painted targets in the training data, the multi-spectral approach performs not always better than the tri-chromatic approach. It is concluded that to get the best results it is necessary to add more special colors to the training data set besides the 24-color Macbeth ColorChecker to improve the performance of the pseudo inverse method for Oriental water color painting.

Introduction

Oriental water color painting makes use of different papers and colorants from Western water color. The paper used is semi-translucent rice paper. The colorants can be mineral-based pigments or dyes from plants. It has already been noticed in previous digital archive work that certain colors in Oriental watercolor painting are not recorded well by a digital camera with the tri-chromatic method, providing good subject matter for further exploration using multi-spectral technology.[1] It is the purpose of this preliminary study to find out the feasibility of using basic multi-spectral technology to capture Oriental water color painting.

There is a great difference between the uses of color in Western and Oriental painting. In Oriental color painting, black ink is the framework forming the outline. The amount of water mixed in the black ink makes it thinner or thicker, consequently lighter or darker. Pigments or dyes are applied to build up the colors. Again, the amount of water and black ink mixed with the color material will vary the shade of the color. The black ink is made from either pine soot or lampblack. The color pigments are made from various minerals, like Azurite and flemish white. One commonly used color, Rattan Yellow, is uniquely derived from the sap of the rattan plant.[2, 3] With such distinct characteristics of an ancient tradition it is of great interest to apply modern digital reproduction technology for archiving purposes.

With the rapid development of the high resolution digital camera, it is more realistic to capture color art works by digital camera.[4, 5] However, a transformation model is needed to convert the digital camera's device signals like R, G and B into colorimetric values of the captured objects. Even though the approach to conventional image capture is mostly tri-chromatic, there are new multi-spectral approaches to capturing images.[6, 7, 8] With such special color materials in Oriental water color painting it is assumed that the spectral-based approach ought to have an inherently better performance than the tri-chromatic approach. To test this assumption, both the tri-chromatic approach with a polynomial model and the multi-spectral approach with a pseudo inverse model are being used in this study. [8, 9] CIELAB color differences have been calculated between the measured and the reproduced colorimetric values of the tested targets.

In this study of Oriental water color painting it is intended to use a commercially available digital camera with a less complicated configuration to establish a preliminary reference.

Transformation Methods

The reflectance of an object, denoted as R(λ), can be represented by a vector space in the visible spectrum with certain wavelength increments. This vector can be reconstructed by several basis vectors through linear modeling techniques. Prior study using Principal Component Analysis has indicated that five to eight basis vectors are sufficient to reconstruct the spectral reflectance accurately for artwork.[8] It is common for most commercial available digital cameras to have only three signal channels, like r, g, and b. These digital signals **RGB** are the results of the linear combination for the spectral sensitivity of the camera, **C(λ)** and the input reflectance of the object, **R(λ)** as

$$\mathbf{RGB = R(\lambda) \times C(\lambda)}$$

To generate more than three signal channels to create five to eight channels representing the basis vectors, multi-image technique is used by taking separate shots with different sets of absorption filter or multi-illumination.[8] While two sets of images can create six channels of digital signals, it is also noted that six eigenvectors can have a cumulative contribution of more than 99%.[8] These digital counts using the multi-image technique can be denoted as **D**. By using the pseudo inverse method[8, 10] it is possible to represent this reproduction system with a transformation matrix **T** that

$$\mathbf{T = R \times PINV(D)}$$

This **R** represents the reflectances of known objects, which can be referred to as the training data set. The **PINV** function is the pseudo inverse function that can be implemented by the MATLAB program. In predicting the results of testing the model, the estimated reflectances of the unknown objects (which can be referred to as the testing data set) can be back calculated as

$$\mathbf{Estimated\ R = T \times D}$$

Estimated colorimetric values can then be calculated through the estimated reflectances. Color difference values can be calculated between the measured and the estimated values to give an indication of the model performance.

Another tri-chromatic approach[9] applies polynomial regression with least squares fitting such that a transformation matrix **(M)** can be used to the correlate the 3-channel digital counts **(RGB)** to colorimetric values **(XYZ)** of the captured objects as

$$\mathbf{XYZ = M \times RGB}$$

The least-squares solution allows to minimize the prediction error and this can be calculated as

$$\mathbf{M = (RGB^T \quad RGB)^{-1}\ RGB^T\ XYZ}$$

In deriving the transformation matrix, the measured colorimetric values and resulting digital counts from the digital camera of the training data set are used. The polynomial terms for r, g and b signals can be of different levels of complexity like

$$RGB_3 = [r\ g\ b]$$
$$RGB_8 = [r\ g\ b\ rg\ rb\ gb\ rgb\ 1]$$
$$RGB_9 = [r\ g\ b\ rg\ rb\ gb\ r^2\ g^2\ b^2]$$
$$RGB_{11} = [r\ g\ b\ rg\ rb\ gb\ r^2\ g^2\ b^2\ rgb\ 1]$$

In this study 3x8, 3x9 and 3x11 terms are used in the polynomial models. The estimated colorimetric values can be shown as:

$$\mathbf{Estimated\ XYZ = M \times RGB}$$

By using the testing data set, the estimated colorimetric values can be calculated directly from the digital camera's r, g, and b values through the transformation matrix. Color difference values can be calculated between the measured and the estimated values to give an indication of the model performance.

Experimental

Six commonly used colors on Oriental water color palettes were selected as the primary colors. As listed in Table 1, they cover the hues from red, orange, yellow and green to blue in addition to white. Mixed with water and black ink, each color was taken to obtain four different shades. A total of 24 color patches were used as the "painted targets".

Table 1. List of the painted Oriental water colors.

No.	Color	Technical term
1	Red	Crimson Lake
2	Orange	Rose Madder
3	Yellow	Rattan Yellow
4	Green	Emerald Green
5	Blue	Azurite
6	White	Flemish White

Spectral reflectance values for all painted targets and all patches on a Macbeth ColorChecker were measured by a GretagMacbeth SpectroEye colorimeter (10nm wavelength resolution). A pair of Macbeth Solar lights was placed at 45 degrees evenly on each side for illumination. A Canon 5D digital camera captured the image into raw file format. Both Macbeth ColorChecker and the painted targets were captured twice under the Solar light with and without the D65 filter (simulating illuminant A) to generate the multi-illumination configuration (six channels).

The Raw RGB image files were converted linearly to a 16-bit TIFF file. Fifty by fifty pixels were read and averaged to become the digital counts for each color patch by a MATLAB program. Consequent computations were all performed in a MATLAB environment. CIELAB color difference values were calculated as indication of colorimetric accuracy. As listed in Table 2, four iterations were performed to test the effectiveness of using various training data sets, and this was further verified against the testing data sets.

Table 2. List of the Training data and Testing data for each Iteration (CC: Macbeth ColorChecker, PT: painted targets)

Iteration	Training Data	Testing data
1	CC	CC
2	PT	PT
3	CC	PT
4	CC + PT	PT

Results and Discussion

These tests have been performed progressively from basic training data to more complicated data sets. Table 3 lists the test results using the Macbeth ColorChecker as the training data to establish the transformation model, using the ColorChecker itself as the testing data. It is noted that, as the number of terms in the polynomial model increases, the performance increases. As a benchmark, Katoh optimized a 3CCD color-video camera to achieve an average ΔE^*_{ab} of 5.6 and a maximum of 14.0 for characterizing the Macbeth ColorChecker.[11] This is very close to the results in the 3 x 11 polynomial model in Table 3. Another benchmark can be referred to Burns[5], where a PCA technique was used to achieve an average ΔE^*_{ab} of 2.2 and a maximum of 4.7 for characterizing the Macbeth ColorChecker. This is also very similar to the results of the pseudo inversion model in Table 3.

Table 3. Modeling results by using the ColorChecker as both the training data set and the testing data set (CC→CC).

Model	Average ΔE	Max. ΔE
3 × 8	13.78	37.97
3 × 9	10.26	41.42
3 × 11	5.94	13.72
P. Inv.	2.28	4.47

Table 4 lists the test results using the painted targets as the training data to build the model and then using them as the testing data to verify the results. In the polynomial method, the model performance does not increase significantly as the number of terms increases to eleven. Compared with Table 3 one can see that most of the maximum errors increase in Table 4. Furthermore, the pseudo inverse model does not perform as well for the painted targets as for the ColorChecker. It is possible that the less uniformity of the hand-made painted targets has introduced noise that causes the poor model performance. However, the polynomial method seems less influenced by the noise created by this lack of uniformity.

Table 4. Modeling results using Painted Targets as both the training data set and as the testing data set (PT→PT).

Model	Average ΔE	Max. ΔE
3 × 8	13.54	54.37
3 × 9	8.60	25.56
3 × 11	8.18	22.79
P. Inv.	6.25	19.22

It is a common practice to use the Macbeth ColorChecker as training data and certain other data as independent testing data. Ideally, a general model can be applied to any kind of testing data. However, this is not the case in this study, as shown in Table 5, where the ColorChecker is used as the training data and the painted targets as the testing data. Compared with the previous two tables one can notice that the average values for the color difference increase for the more complicated polynomial models (3x9 and 3x11). There are sizeable jumps also in the color difference values for the pseudo inverse model, which indicates a poor model performance in such settings and implies that the ColorChecker alone is insufficient as the training data set for modeling Oriental water color.

Table 5. Modeling results of using the ColorChecker as the training data set and the Painted Targets as the testing data set (CC→PT).

Model	Average ΔE	Max. ΔE
3 × 8	12.43	27.74
3 × 9	12.04	28.60
3 × 11	10.25	19.61
P. Inv.	9.79	25.44

One more test has been performed taking both the ColorChecker and the painted targets as the training data set and used the painted targets also as the testing data set (CC+PT→PT). The average color difference values as shown in Table 6 are lower in general than those in Table 5. However for the 3x8 polynomial model the maximum color difference value is increased. For the 3x11 polynomial model the maximum color difference value is decreased. It is possible that more complicated model like 3x11 is needed when adding the painted targets into the training data set.

Table 6 also shows that for the pseudo inverse model adding the painted targets into the training data set actually increases the model performance as compared with results in Table 5. One may notice that using the spectral-based pseudo inverse model produces the best performance with the smallest average color difference overall. On the other hand, the 3x11 polynomial model seems to generate less maximum errors than the pseudo inverse model regardless the painted targets are in the training data set or not, as shown in Tables 5 and 6.

Table 6. Modeling results of using the ColorChecker and the Painted Targets as the training data set and the Painted Targets also as the testing data set (CC+PT→PT).

Model	Average ΔE	Max. ΔE
3 × 8	15.07	64.19
3 × 9	9.47	39.05
3 × 11	7.56	16.96
P. Inv.	6.79	20.02

For the pseudo inversion model the maximum error has been found in a blue color patch (color No. 13). For comparing their characteristics, the original, the first estimated (CC→PT), the second estimated (PT→PT), and the third estimated (CC+PT→PT) spectral curves are plotted together as shown in Fig. 1. One can notice that when using only the ColorChecker as the training target (CC→PT), the estimated spectral reflectance of the blue color for Oriental water color is vibrating significantly, creating a big error. However when using the painted target as the training data (PT→PT), the estimated reflectance matches with the original reflectance quite well. It indicates that using the ColorChecker alone as the training data set in the pseudo inverse model is insufficient to handle the blue color for Oriental water color.

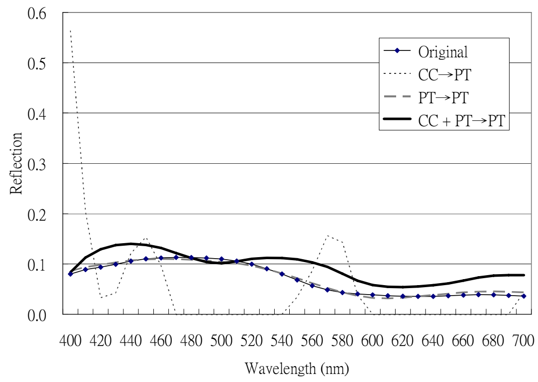

Fig. 1. Rreflectance curves of the originl, the first estimated (CC→PT), the second estimated (CC→PT), and the third estimated (CC+PT→PT) spectral values for a blue color in painted Oriental water color by the pseudo inverse model.

All the testing results for the painted targets in those three iterations by the pseudo inverse model are shown in Fig. 2. It can be seen that the testing results are improved when the painted targets are added to the training data set.

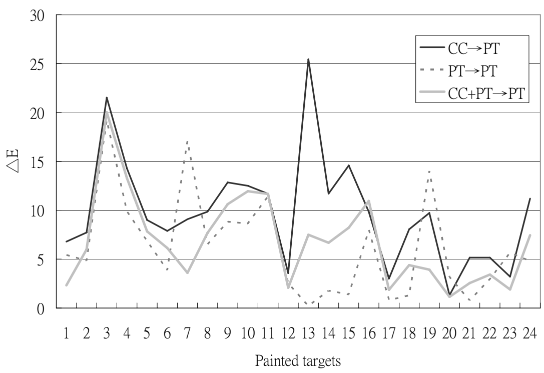

Fig. 2. Testing results for all painted targets by using the pseudo inverse model (No. 13 is the blue color referred in Fig. 1).

Conclusion

Both multi-spectral and tri-chromatic approaches have been used to capture Oriental water color painting with a digital camera. Different iterations have been tested to exclude or include the painted targets in the training data set. It is concluded that when the painted targets are included in the training data set, the spectral-based pseudo inverse model performs better than the tri-chromatic polynomial model. When using only the Macbeth ColorChecker as the training data set, the pseudo inverse model performs slightly better than the polynomial model. Therefore it is suggested that better results can be achieved by applying the spectral-based pseudo inverse model when using both the painted targets and the commonly used Macbeth ColorChecker as the training data for Oriental water color. Without the special painted Oriental water color patches, the pseudo inverse model can perform only to a certain level.

It is possible that other color targets like GretagMacbeth ColorChecker DC can serve better as the training data since they include wider selections of color samples. More complicated models can also perform better. Finding a way to improve uniformity on the painted targets and thus to reduce the noise getting into the model remains an issue to work on in the future.

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