

A Smart Palette for Helping Novice Painters to Mix Physical Watercolor Pigments

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Abstract

For novice painters, color mixing is a necessary skill which takes many years to learn. To get the skill easily, we design a system, a smart palette, to help them learn quickly. Our system is based on physical watercolor pigments, and we use a spectrometer to measure the transmittance and reflectance of watercolor pigments and collect a color mixing dataset. Moreover, we use deep neural network (DNN) to train a color mixing model. After that, using the model to predict a large amount of color mixing data creates a lookup table for color matching. In the smart palette, users can select a target color from an input image; then, the smart palette will find the nearest color, which is a matched color, and show a recipe where two pigments and their respective quantities can be mixed to get that color.

CCS Concepts

•Applied computing → Fine arts; Fine arts; •Computing methodologies → Neural networks;

1. Introduction

Color mixing is a difficult thing for novice painters. Because they must understand how to portray the colors of a scenery or a still life by color mixing. In addition, one may need to know the properties of paint pigments, namely transparency, semi-transparency and opacity, and how to select the appropriate colors on a palette, which usually has dozens of pigments.

Most color mixing studies use both Kubelka [Kub48] and Duncan method [Dun40] to compute the absorption and scattering of pigments to get a new mixture. For example, Aharoni-Mack et al. [AAMSL17] utilize it to mix watercolor color for recoloring painting. Moreover, Xu et al. [XTJ*07] use Kubelka method and neural network to predict the mixing pigments.

To help novices learn the skill of color mixing, we build a system which is based on physical watercolor pigments. Users can pick a target color, in RGB model, from an input image and then our system will find the nearest color and its recipe. In this work, we create a dataset of physical watercolor pigments and use DNN to train a color mixing model, in Section 2. Finally, we use the model to predict pigment mixing to build a lookup table for color matching, in Section 3.

2. Color Mixing of Physical Watercolor Pigments

Watercolor pigments have more transparent property than other painting material. Because a pigment has transparency, the result-

ing color will be affected by paper. In addition, pigment thickness can also cause differences in transparency.

2.1. A Database of Watercolor Pigments

In our experiment, we use thirteen pigments which are commonly used by painters. There are cadmium red ρ_1 , alizarin crimson ρ_2 , burnt sienna ρ_3 , lemon yellow ρ_4 , cadmium yellow ρ_5 , raw sienna ρ_6 , sap green ρ_7 , cerulean blue ρ_8 , cobalt blue ρ_9 , ultramarine ρ_{10} , prussian blue ρ_{11} ivory black ρ_{12} and chinese white ρ_{13} , and the brand of watercolor pigment is Winsor and Newton. Then, each pigment takes twelve different quantities, 0.01ml, 0.02ml, ..., 0.10ml, 0.12ml and 0.16ml, and then we coat them in the grids of white paper, Canson Ca grain, and transparent film, each grid size is 1.5×1.5 centimeter. To get more accurate pigment samples, we use a silicone wide-firm flat brush, which is like a flat scraper with pliability, to replace traditional brush and avoid pigment remains on the brush. In addition, we use a syringe with a one-milliliter capacity to measure pigment quantities. After that, we use a SD1220 spectrometer; and its wavelength is from 380 nm to 780 nm. It have the light source box and the K1 light source; both are the same light source to measure the transmittance and reflectance of the samples of watercolor pigments respectively. In our work, we take 41 wavelength points, per 10 wavelength pitch to sample one, to denote a measured data.

Two types of color mixing in our dataset: type one is the same primary pigments to mix, namely increased pigment quantity; for example, 0.01ml plus 0.01ml equals 0.02ml. Type two means two

different primary pigments to mix. The combination ratios are 1 to 1 and 1 to 2 (similarly 1 to 2); for example, the ratio of 1 to 1 includes 0.01ml and 0.01ml, 0.02ml and 0.02ml, 0.04ml and 0.04ml and 0.08ml and 0.08ml. Our color mixing dataset has 399 measured data in type one and 644 measured data in type two.

2.2. Color Mixing by Deep Neural Network

We use 207 features as input which is the transmittance, reflectance, quantity of two pigments and paper reflectance. The color mixing model has 7 hidden layers, which are 100, 80, 80, 70, 70, 60 and 60 neurons respectively, and 100,000 epochs are used. In the hidden layers of first, third, fifth and seventh, we use softsign as activation function; the others use tanh. The output is a mixed pigment with 41 sample wavelength. Adam is our optimizer and its learning rate is used 0.001. The loss function use mean square error and L2-norm is a regularization term. In our experiment, 782 training data and 261 testing data are used.

3. A Smart Palette

For novice painters to get the skill of color mixing easily, we design a smart palette by our color mixing model and a lookup table to achieve the goal.

3.1. Building a Lookup Table for Color Matching

We use an interpolation method to generate more primary pigments at 0.002 intervals; then, using color mixing model to predict their mixture, which will take about an hour in prediction from two processes (Intel(R) Xeon(R) E5-2650 v3 with 2.30GHz CPU). Finally, we build a lookup table, which has 75,088 data of the same primary pigment to mix, namely increased pigment quantity, and 1000 × 1000 data of two different primary pigments to mix.

3.2. User Interface of a Smart Palette

In the system, users can select any image type of that they want to draw, whether a portrayed scenery or still life. In Fig. 1, a target color is selected from a red circle of an input image in part E and the resulting recipe is shown in part B and C. Thus, we can derive that an RGB value (63, 92, 44) can be matched by RGB value (62, 95, 44) in the color space of 13 watercolor pigments and its ingredient is 0.014 ml of cadmium yellow hue and 0.012ml of cerulean blue hue and it takes one second to find the matched color on a desktop computer (Intel(R) Xeon(R) E3-1231 v3 with 3.40GHz CPU). More cases are shown in Fig. 2.

4. Conclusion

We design a system which is based on physical watercolor pigments to help novice painters to get the necessary skill easily. Because color mixing is a difficult problem therefore we will report on arbitrary color mixing of two watercolor pigments in the future.

5. Acknowledgments

This project was partially supported by MOST No. 106-3114-E-002-012, No. 105-2221-E-002-128-MY2 and MediaTech.

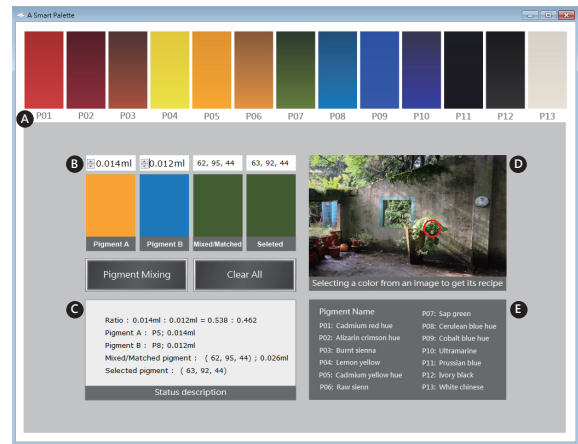


Figure 1: A smart palette. It is divided into five parts. In part A, users can select 13 pigments with different quantities, each grid is a gradient, where at the top is the color of 0.16ml and at the bottom is the color of 0.01ml. Part B shows a result of color mixing or color matching and its ingredient pigment. The user can find more information about color mixing or color matching in part C and select a target color from an image in part D. Finally, users can get pigment name in part E and then use them to mix color in the real world.

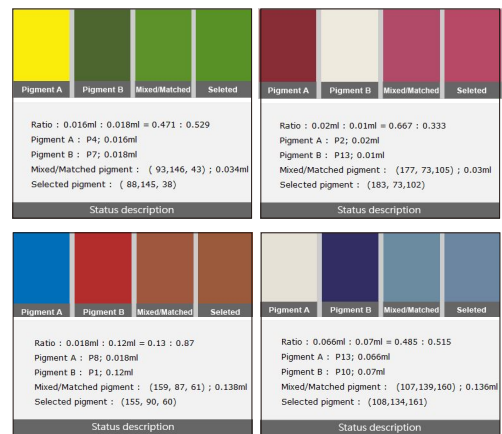


Figure 2: The Four cases of color matching.

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