Multispectral Image Segmentation of Paintings Drawn with Natural Mineral Pigments Using the Kernel Based Nonlinear Subspace Method

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Abstract

Many, historically or archeologically valuable paintings such as wall paintings in ancient tombs or Buddhist paintings in Japan or the other Asian countries have been drawn with natural mineral pigments (NMP). The digital archive of those paintings, the identification of pigments used in the paintings and the retrieval of color fading are strongly desired. Multispectral image acquisition of those paintings is very useful for both archive and analysis purposes. In this paper, we focus on the segmentation by pigment from multispectral images in the visible range. Here the kernel based nonlinear subspace method (KNS) is applied to the pigment-based segmentation of multispectral images of the paintings. At first, 55 NMP patches were made and the spectral reflectances were measured. Next, multispectral image acquisition of the color patch array and a Buddha painting drawn with those pigments were performed. Using the training sets of color patches, the segmentation of those images was performed. For comparison, image segmentation from three-band image and a conventional linear subspace method called CLAFIC were tested. It was found that the KNS method with multispectral images worked best than the other methods. Quantitative evaluation with color patches was carried out and the visual evaluation for the segmentation result of the Buddha painting was also performed.

Introduction

Many, historically or archeologically valuable paintings such as wall paintings in ancient tombs or Buddhist paintings in Japan or the other Asian countries have been drawn with natural mineral pigments (NMP). The digital archive of those paintings, the identification of pigments used in the paintings and the retrieval of color fading are strongly desired. Conventionally the image acquisition of such contents has often been done with an RGB camera. However, the RGB camera is not sufficient for the purposes of digital archive and analysis.

Multispectral image acquisition of those paintings is very useful for both purposes. Digital archive in a form of spectral reflectance image allows the accurate color reproduction of those paintings in the current status [1]. On the other hand, spectral information reflected from the object contains rich information compared with RGB image. Such information has potential in analysis of identification of the used pigment or the estimating the way of making use of those pigments [2-4]. In fact, infrared imaging, fluoroscope imaging or X-ray spectral analysis have been done for the analysis purpose. However, the multispectral images over visible range which are acquired for the purpose of accurate archive and color reproduction should also contribute the analysis as well.

In this paper, we focus on the possibility of analysis of pigment identification from multispectral images in the visible range. We develop a method for segmenting the painting based on pigments. Very few study on the multispectral image acquisition for those subjects have been done so far. Typical NMPs are azurite (mountain blue), malachite (mountain green), cinnabar (HgS), etc. The natural mineral pigment is made by grinding a rock. Even if the original rock is identical, the color depends on the grain size of the ground rock. Sometime the ground pigment is further burned to make a darker color. Namely, even if the source rock is the same, the appeared color is different. This variation makes the identification of the pigment difficult.

In this paper, the characteristics of the spectral reflectance of many kinds of NMPs are first investigated. We collected sets of NMPs from two different manufacturers and made color patches by mixing the ground rock with glue. Spectral reflectances are then measured. We next perform multispectral image acquisition of those patches and a Buddha painting drawn with those pigments. We adopted the kernel based nonlinear subspace method to classify each pixel in the multispectral image into one of predetermined categories.

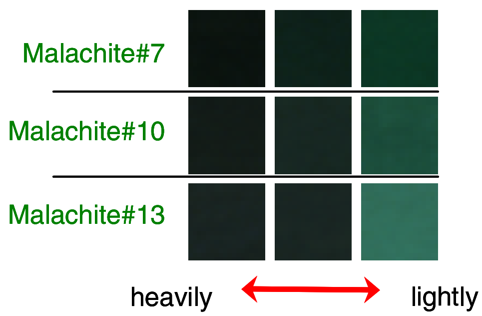
Preparation of natural mineral pigments and spectral reflectance measurement

A set of natural mineral pigments was collected which inludes 55 pigments. 55 color patches were made by mixing the ground rock with glue. Figure 1 shows a photograph of the color patch array.

In this set, cinnabar, azurite and malachite have respectively five, five and six different grain sizes. Five cinnabar, five azurite and six malachite are placed in the left-most column, second column, and third column and bottom of the fourth column, respectively, in Fig. 1. Furthermore, azurite and malachite have burned ones in different degree. Those patches are placed in the three rightmost columns in Fig. 1. Fig. 2 shows an array of some color patches cut out from the original photograph. In this figure, the color variation by grain size and burning are demonstrated.

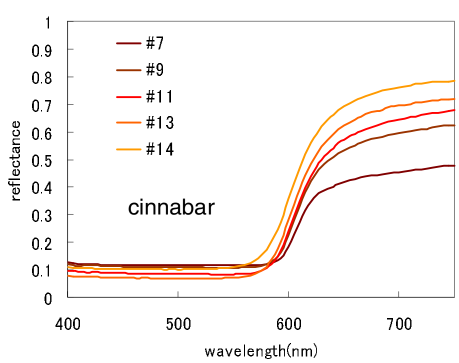
Fig. 1 Color patches of natural mineral pigment.

Color change by grain size

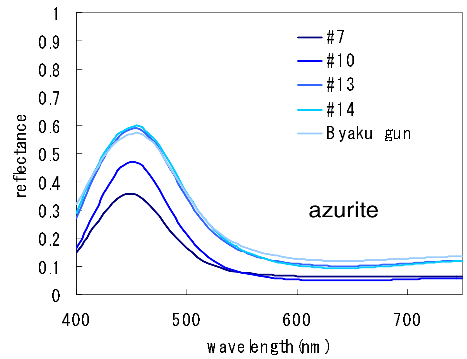


Color change by burning

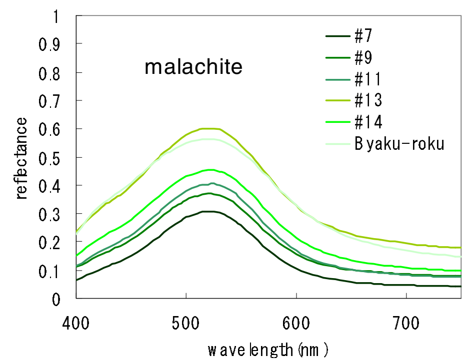
Fig. 2 Color variation by grain size and burning.



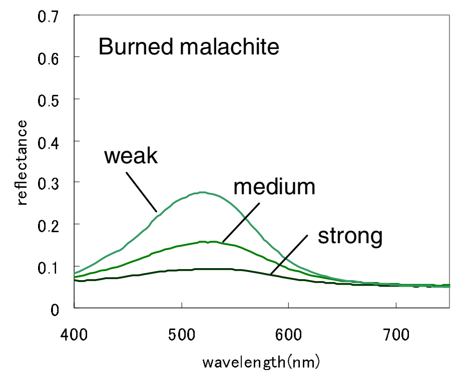
(a) Cinnabar with different grain size



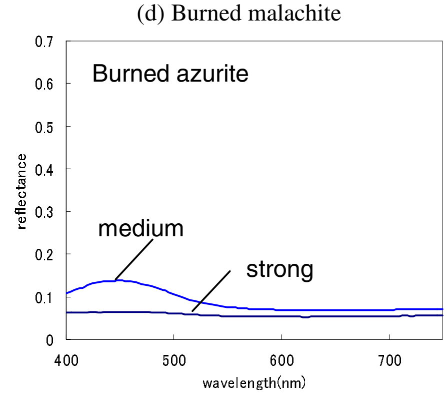
(b) Azurite with different grain size



(c) Malachite with different grain size



(d) Burned malachite



(e) Burned azurite

Fig. 3 Variation of spectral reflectance by grain size and burning.

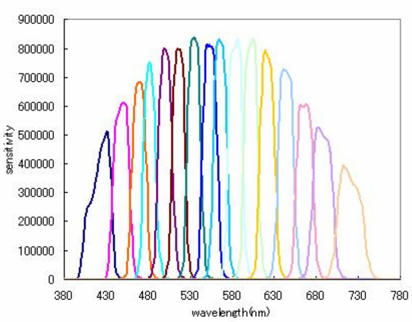
Generally the smaller the gain is, the less saturated the color is. Each of commercially available natural mineral pigment has a number related to the grain size, where the larger number corresponds to smaller grain. Figure 3 (a)-(c) shows the grain size dependency of spectral reflectance. For the purpose of pigment identification, the stable classification independent from the grain size is desired. So first we thought to model the change in reflectance by transformation by a logarithmic function or other normalization techniques. However, it was difficult to find any model that fit to all kinds of color variation.

Figure 3 (d), (e) show the change in spectral reflectance by burning. Burning makes the material be oxidized and its color darker. In this case, it also seemed difficult to model the color change. So we decided to adopt not a model-based but sample-based statistical classification method as described in the later section.

Multispectral image acquisition and estimation of spectral reflectance

Multispectral image acquisition was performed for the color patch array and a Buddha painting drawn with the NMPs collected. A 16 band camera developed by Olympus in collaboration with the Natural Vision project [5] was used in image acquisition. The image size of this camera is 2048 x 2048 pixels and the quantization depth is 12 bits/pixel/band. In Fig. 4 the set up of image acquisition is shown in the left and spectral sensitivities of 16 bands are shown in the right. From the captured images, spectral reflectance was estimated pixel by pixel. Wiener estimation technique was used [6].

(a) Setup for image acquisition



(b) Spectral sensitivities of 16 band camera

Figure 4 Setup and sensitivities of Multispectral image acquisition.

Segmentation method

For a multi-category discrimination problem, the subspace method is generally effective. A typical subspace method is the CLAFIC method [7]. In this method, a subspace corresponding to each category is calculated in advance as a subspace spanned by a limited number of principal components of the training samples. A test target is projected onto each subspace and classified into the category in which the norm of the vector projected from the target to the subspace is the maximum. This method does not work in case that distribution of samples in the category is along a nonlinear axis.

Tsuda [8] and Maeda and Murase [9,10] independently proposed to combine the kernel method [11,12] and the subspace method. Maeda called their method the kernel based nonlinear subspace method (KNS). We tried to apply the KNS method in classification of the NMP. In this section, the KNS method is reviewed.

Let us denote the spectral reflectance a vector $\mathbf{x}$ in a d dimensional space. The purpose here is to classify the spectral reflectance vector at each pixel of the multispectral image into a proper category of NMP. In the kernel method, a vector is mapped to a higher dimensional space using nonlinear functions as

$$\varphi : \mathbf{x} \mapsto \varphi(\mathbf{x}) = (\varphi_1(\mathbf{x}), \ldots, \varphi_{d_\varphi}(\mathbf{x}))^t \qquad (1)$$

Here a kernel function is defined as an inner product of two vectors in the higher dimensional space:

$$k(\mathbf{x}, \mathbf{y}) = \varphi(\mathbf{x})^t \varphi(\mathbf{y}) = \sum_{i=1}^{d_\varphi} \varphi_i(\mathbf{x}) \varphi_i(\mathbf{y}) \, . \qquad (2)$$

There are some kernel functions suitable in the kernel method. In this paper, we use the following polynomial function.

$$k(\mathbf{x}, \mathbf{y}) = (\mathbf{x}^t \mathbf{y})^p \qquad (3)$$

Non-linear transformation used in the kernel method has two features. One is that the transformed space is very high dimension. As a result, each axis in this high dimensional space becomes linearly independent and it is expected that there exits a hyperplane suitable for discrimination. The other is that if the problem is formulated using a kernel function, it can be solved by the operation between the vectors in the low dimensional space without calculating the mapping by φ explicitly.

In order to construct a class nonlinear subspace using a kernel function, we use a technique of kernel nonlinear principal component analysis proposed by Schölkopf [11]. Eigen vectors and eigen values of a set of higher dimensional training vectors are calculated for each category in advance. For each test vector, the projection onto each class nonlinear subspace is performed and the norm of the vector is calculated. The following is the mathematical form of such procedure.

$$P^{(k)}(\mathbf{x}_{test}) = \sum_{i=1}^{d'} (\mathbf{v}_i^{(k)t}(\mathbf{x}_{test}))^2 = \left\| (\Lambda_{d'}^{(k)})^{-1} \mathbf{U}_{d'}^{(k)t} \mathbf{X}_\phi^{(k)t} \varphi(\mathbf{x}_{test}) \right\|^2 \qquad (4)$$

Here, $X_f^{(k)}$ is a matrix whose column is higher dimensional vector of training sample in kth category. Vector $\mathbf{v}_i^{(k)}$ and matrices $\Lambda_{d'}^{(k)}$, $\mathbf{U}_{d'}^{(k)}$ in Eq. (4) are calculated from the singular value decomposition of represented as

$$\mathbf{X}_\phi^{(k)} = \mathbf{V}^{(k)} \Lambda^{(k)} \mathbf{U}^{(k)t} \, . \qquad (5)$$

In Eq. (4), $\mathbf{X}_\phi^{(k)t} \varphi(\mathbf{x})$ can be calculated without explicit calculation of φ as follows.

$$
\mathbf{X}_{\phi}^{(k)t}\varphi(\mathbf{x}) = \begin{bmatrix} \varphi(\mathbf{x}_1^{(k)})^t \\ \vdots \\ \varphi(\mathbf{x}_n^{(k)})^t \end{bmatrix} \varphi(\mathbf{x}) = \begin{bmatrix} k(\varphi(\mathbf{x}_1^{(k)}),\varphi(\mathbf{x}_{test})) \\ \vdots \\ k(\varphi(\mathbf{x}_n^{(k)}),\varphi(\mathbf{x}_{test})) \end{bmatrix} = \begin{bmatrix} (\mathbf{x}_1^{(k)t}\mathbf{x}_{test})^p \\ \vdots \\ (\mathbf{x}_n^{(k)t}\mathbf{x}_{test})^p \end{bmatrix} \tag{6}
$$

Singular values and vectors of $\mathbf{X}_{\phi}^{(k)}$ can also be calculated without explicit calculation of φ because any inner product of high dimensional vectors is replaced by the kernel function of the inner product of the low dimensional vectors.

Equation (4) is evaluated for all categories and the test vector is assigned to the category which provides the maximum value. Figure 6 shows schematic illustration of the kernel based nonlinear subspace method

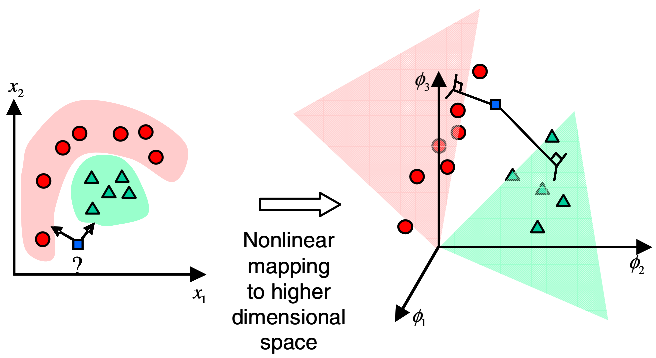


Fig. 6 Schematic illustration of the kernel based nonlinear subspace method.

Segmentation experiment and result

16 band images of the 55 NMP patch array shown in Fig. 1 and a Buddha image drawn with the same NMP were taken by the 16 band camera. Buddha image is shown in Fig. 7 left. For Buddha image, it was recorded by the painter what pigment was used in each region. This record was used in the later evaluation of segmentation accuracy. Fig. 7 right shows the color patches cut-out from the original image so as to evaluate segmentation accuracy easily.

As a preliminary study of segmentation of NMP, we aimed segmentation of three typical NMPs namely, azurite (mountain blue), malachite (mountain green), cinnabar (HgS). For remaining NMP, six categories: "ancient red", "ocher", "brown", "red", "black", "white" were prepared. 25 pixels for each color patch were extracted and used as training data. For evaluation, 100 pixels different from training data were tested for each color patch if it was categorized correctly.

In this paper, the two points were studied; effectiveness of multispectral imaging over three-band imaging for segmentation, effectiveness of introduction of the kernel method over linear segmentation method. For the first point, three band images were artificially generated from multispectral images. Namely, first spectral reflectance was estimated pixel-by-pixel from 16 band images, next, by multiplying rgb-color matching function, three band image was generated. For the second point, the CLAFIC method was evaluated as a linear segmentation method.

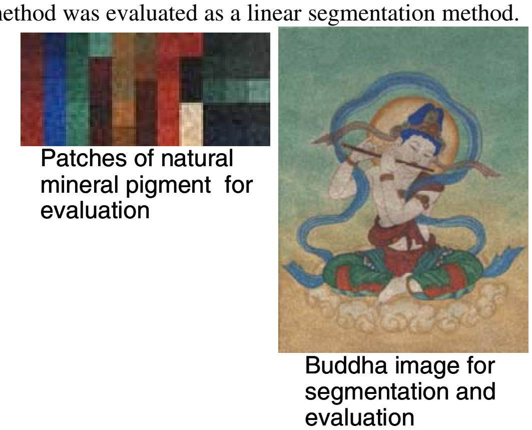


Fig. 7 Patch and image used in segmentation and evaluation.

There are some parameters in each method. In the CLAFIC method, dimension of subspace used in the segmentation must be determined. In the kernel method, the exponent, *d,* of kernel function as well as the dimension of subspace must be determined. In this study, all possible parameters were tested and the ones that provide the best segmentation accuracy were listed. Quantitative evaluation of segmentation accuracy is shown in table 1. The conditions shown below the accuracy denote the parameters which give the best result in each segmentation method.

Four combinations were tested. In the comparison between three bands and 16 bands, 16 band images achieve much higher segmentation accuracy than 3 band images. The effectiveness of multispectral imaging for segmentation is obvious.

Introduction of the kernel method also leads to improvement of accuracy although its degree is smaller than the multispectral imaging.

Table 1 Segmentation accuracy.

		Number of band	
		3	16
method	CLAFIC	64.5% (dim. of subspace: 1)	93.0% (dim. of subspace: 3)
	Kernel	75.1% (exponent, d=12, dim. of subspace: 25)	98.7% (exponent, d=2, dim. of subspace: 28)

The pseudo-colored segmentation results are shown in Fig. 8. The result by the three-band CLAFIC method is clearly poor. For color patch, the three-band Kernel or the 16-band CLAFIC show noisy segmentation pattern. It can be seen that the 16-band kernel provides the best segmentation result for color patch.

For Buddha image, it is not easy to say which segmentation is the best. However, by close observation of the images, it is found that the 16-band kernel method gives the smoothest segmentation result. This is supposedly because in the 16-band kernel method the clusters of each NMP in the Buddha painting are separated definitely in the high dimensional space.

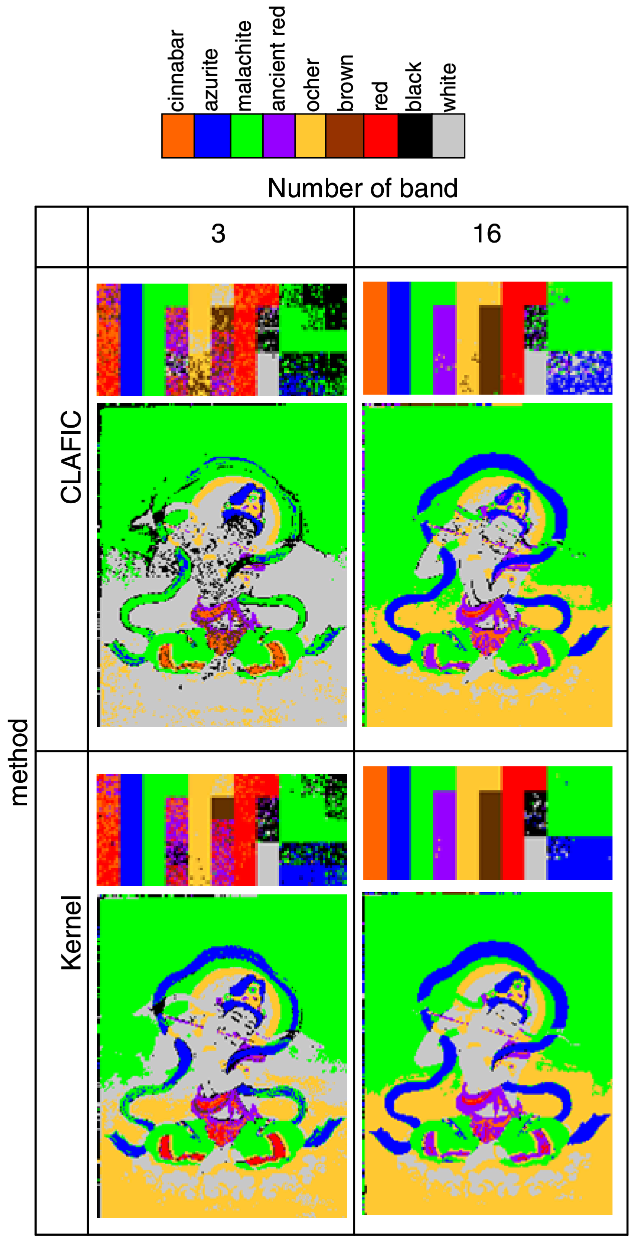


Fig. 8 Pseudo-colored segmentation result. Nine categories are pseudo-colored as indicated in the top row.

Conclusions

In this paper, we proposed to apply the kernel based nonlinear subspace method (KNS) in the pigment-based segmentation of multispectral images of the paintings drawn with NMPs. At first, 55 NMP patches were made and the spectral reflectances were then measured. We next performed multispectral image acquisition of that color patch array and a Buddha painting drawn with those pigments. Using the training sets of color patches, the segmentation of those images was performed. It was confirmed that the KNS method works well in segmentation of multispectral images of the paintings drawn with NMPs.

Hereafter applicability of the method to the other paintings also needs to be investigated.

Acknowledgement

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Author Biography

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