伝統色特徴分析機能を有するアート画像探索・閲覧システム

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現在，多くの美術品の画像が作者，製作年代，製作地などの付加情報とともに公開され，付加情報（属性）に基づいたキーワード検索システムも提供されている．本稿では，それら属性と画像の色の特徴との間の関連性に着目し，色合いの僅かな違いが鑑賞のポイントとなる美術品の画像を対象として，一般的な画像検索システムとは異なるユーザインタフェース持つ画像探索・閲覧システムを提案する．本システムの特徴は，注目する画像の色の微妙な違いを，色分布のズーム機能と伝統色による評価機能を用いて可視化することにより，人が画像を分析・鑑賞する際の受容の多様性をサポートする点にある．

An Image Exploring System with Culture-dependent Color Analysis and its Application for Fine Art

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There are vast amounts of images archived in on-line museums with annotation data such as author and era. These images with annotation data can be explored by current keyword-based search systems. In this paper, we focus on the relations between the annotation data and color features of art images, and propose an art image exploring system with a user interface different from general image retrieval system. We represent an art image exploring system which enables users to capture characteristic colors of each image and subtle differences between images based on culture. In addition, the system visualizes the subtle differences of colors in images with a zooming function for color distribution and cultural-color name estimation.

1. Introduction

In the current cyber spaces, huge digitized media data are archived and accessed via various applications with efficient search methods. In content-based image processing, color is the most important feature, and researchers have studied color content-based image retrieval extensively. However, the degree of color variety differs between cultures, and each color name is designated uniquely in a language [2][10].

On the other hands, when people appreciate an image, they tend to compare it with other images unintentionally. Universally, people's sensibility on the differences between images depends on the cultural background of the people and media. The nature of human perception for media data cannot be processed by single schema in a simple image search system.

The color distribution of an art image is related to the attribute of the image such as author and era in many cases. In addition, the analysis on the subtle color differences between images is one of the important issues for the appreciation of fine art. A new appreciation environment with a user-friendly interface is expected, which provide both an overview map of many images and a visualization of subtle differences among images grouped by annotations.

In the field of image processing and CBIR (Content-based image retrieval) [5][6][22], color is considered as one of the most important features. The color information of each image is extracted as a color histogram and vectorized by a reference color set [30]. The reference colors are defined by colors of the color histogram bins. The number of the color histogram bins should be around 100 for efficient processing [30]. We cannot express, such as art and design, the nuances of color.

Most image retrieval methods using concept terms use annotations or tags attached to images. Alternative methods exist to associate images to concept expressions, including “impressions” extracted from each image by several color combination correlation [1][13][15][23] or extracting weighted words as impressions according to all colors used in each image [13][16]. These methods are particularly applicable to images that have unique compositions and styles, but unable to capture differences of features dynamically because these process the relations between annotations of image and features of image statically.

In this paper, we represent an art image exploring system which enables users to capture characteristic colors of each image and subtle differences between images based on culture. This system leads to a new appreciation environment with adaptability for the diversity of human perception for images, using dynamic comparison and extraction of focused feature.

The process of our system for analyzing target image-groups is consists of the following steps. First, our system provides several grouping keys such as author, city and era included in the annotation of archived images. A user defines an image group using a set of grouping keys. Second, the system compares the image groups each other and extracts distinctive color features. Representative features of each image group are calculated by statistical analysis. Finally, the system outputs the representations of each image group’s characteristic. One is a color histogram to visualize distinctive color features of the image group, and another is a representative image of the image group by similarity calculation.

In addition, for the purpose of processing of human sensibility for colors, our system extracts culture dependent color names from an image using databases of culture-dependent traditional color collection. We have already proposed a method to treat culture-dependent colors by color space transformations and analyze the color diversity and semantics at a concept-level [11].

For color information, the system starts analysis from the overview of the image-groups. First, the system rescans the target images to compute color distribution of the neighborhood colors based on the colors that a user selects for the analysis. Next, the system estimates a set of color names from culture-dependent color names [12]. Finally, the system aggregates and visualizes culture-dependent colors and the similarity between each image-group.

Therefore, the system enables high-level explorative analysis about color features depending on image attributes, such as author, country, era, etc. The representation of color by culture-dependent color names supports people with various cultural backgrounds to easily understand the characteristic of colors of image-groups.

We examine the feasibility and efficiency of our method by applying it to two image collections.

2. Basic functions of our system

Our system has following five functions that provide feature estimation and evaluation with processing of sensibility for colors.

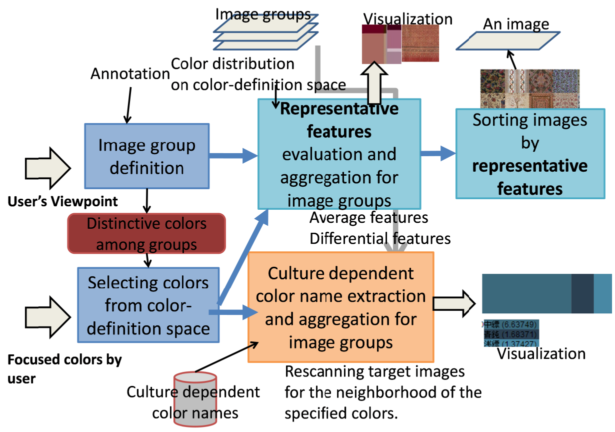


Figure 1. System structure of art image exploring system

(1) Image group definition
(2) Selecting colors from color-definition space
(3) Representative feature evaluation and aggregation for image groups
(4) Culture-dependent color name extraction and aggregation for image groups
(5) Sorting images by representative features

2.1. Image group definition

Generally, most of images are archived with annotation data. In our system, an image group is defined by annotation data. Text annotation such as author, city and era are major grouping keys. Numerical annotation as the spatiotemporal parameter is also useful for grouping images. Users can define the image groups as their viewpoints for the analysis.

2.2. Selecting colors from color-definition space

Target images are vectorized as color histogram with color space quantization as around 100 dimensions. This quantized color space is called "color-definition space" in our system. Users of our system can specify colors for analyses from color-definition space including all colors. We consider that the set of significant colors by valiance analysis is useful for representation of the differences between image groups, and define the set as "distinctive colors".

For calculating distinctive colors, we apply the analysis of variance (ANOVA) method to each color of the color-definition space [11]. The null hypothesis is that the difference between groups' mean values is significant. Distinctive colors are the colors of the null hypothesis. We reject this hypothesis if the p-value (possibility) is 0.01 or less.

2.3. Representative feature evaluation and aggregation for image groups

We provide two aggregation methods for each image group with selected colors. One is averaged color feature calculated as group mean of color distribution for each image group. The other is differential color feature calculated as difference between group mean of color distribution and grand mean of color distribution. Most similar image to representative features is defined as a representative image of each image group.

2.4. Culture-dependent color name extraction and aggregation for image groups

To extract subtle differences on specified color (especially distinctive color) in multiple images, our system rescans target images for creating color histogram of the neighborhood colors of the specified color. The neighborhood distance and granularity of color quantization are optimized for the specified colors and purpose. Based on the recreated color histogram, the system estimates which culture-dependent color name is most similar to the specified color using our transformation method [11][12]. Aggregation of estimation results for each image group can be visualized as subtle differences of color in image groups.

2.5. Sorting images by representative features

User can access individual image sorted by representative features through the easy-to-understand interface. This function also enables the image retrieval based on a specified color.

3. Experiments

In this section, we present several examples of the application using our method to show the applicability of our system.

3.1. Target data and color set

Target data of the experiments is (1) 496 images of textile called 'Chintz' and 'Sarasa' owned in four online museums and one private collection, and (2) 8000 images of Ukiyoe from Tokyo Metropolitan Library [27].

As an experimental environment, we selected 130 colors of Color Image Scale (CIS) [17] to construct Color-definition Space[11] CIS is well designed color system and the number of dimension is suitable for calculating the similarity between images. Each color of CIS has its own short names such as Dull Red (R/Dull) or Strong Purple-Blue (PB/Strong). These color names are useful to specify colors. As culture dependent colors, we selected DIC Color Guide [8] and some color collections [21] are selected.

We calculate the color distance for pixels using the HSV color model, which has an advantage of tractability and algorithmic efficiency. For the color deference between color definitions, the color distance is calculated using CIE2000 formula [18] as far as the performance requirements are fulfilled. The similarity between color distributions is calculated by cosine, which is efficient for computing the distances on sub-space.

These experiments are not intended to lead to any conclusions about Sarasa and Chintz or Ukiyoe, but to show the effectiveness of the proposed method in the range of images collected.

3.2. The results of relative feature evaluation & aggregation for image groups of Chintz collection

Target data of the experiment is image data of textile called 'Chintz' and 'Sarasa' owned in several museums and private collections which have been published on the Web. Chintz and Sarasa were distributed as trade goods from the Age of Discovery in the 16th century. Those were exported from India to each consuming countries at the beginning of the age. Later, those started to be produced in the UK and around the world. In addition, the British East India Company and the Dutch East India Company played a major role in the trade and the production.

For this experiment, we selected the place of production, the place/museum collecting the collections, the market/consuming countries and the era of production as keys for making image groups.

We collected images from online museum sites and collector's blog using search with the terms 'Chintz' and 'Sarasa'('更紗'). We rejected the images of china and porcelain to keep the quality of images and focus on textile. When one item had several images, we selected one image for one item. We collected 828 images and selected 496 images for the experiments. Table 1 shows the data selected.

It should be noted that this experiment is not intended to lead to any conclusions about Sarasa and Chintz, but to show the effectiveness of the proposed method in the range of images collected.

Table 1. Target Images for experiment

Museum / Collection	Country of the Collection	Number of images
Victoria and Albert Museum [28]	U.K.	210
Tokyo National Museum [26]	Japan	146
Private Collection (Nara) [19]	Japan	130
Museum of Toile de Jouy [24]	France	9
Smithsonian American Art Museum [25]	U.S.	1

(1) Examples of Distinctive Color Extraction

In this section, we select 'Manufacture Country' as the key for grouping and show the example of Distinctive Color Extraction.

Figure 3 shows the average of the color distribution vector of selected image group (in this case, all) over the Color-definition space.

Figure 3. 2D-Visualization of Color Distribution Average of Selected Images (Grand Mean)

Third column of Table 2 shows the difference between (the second column) vector average of the color distribution of each group and the vector of Figure 3. We can find that the difference shows clearly the characteristics of each group.

In the fourth column of Table 2, the visualized colors extracted only from the 28 colors that specified by an analysis of variance by a group of manufacture country from colors on Color-definition space, where a significant difference is at 1% level. As can be seen, the number of colors is reduced, and the feature of the group is visualized clearly so that even those who are not familiar with color can understand the distinctive colors of each collection easily.

Table 2. Extracted distinctive-colors of textile products grouped by manufacture country in the form of 2D- Visualization of Color Distribution

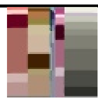
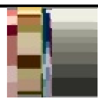
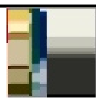
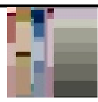
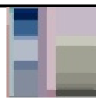
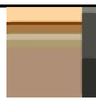
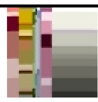
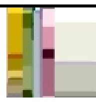
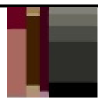
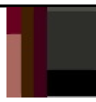
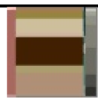
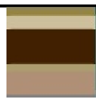
	Group's mean (full color)	Difference from grand mean (full color)	Difference from grand mean (distinctive colors)
India 337 images			 9 colors
U.K. 116 images			 17 colors
Japan 16 images			 6 colors
Indonesia 11 images			 5 colors
France 9 images			 19 colors
Thailand 2 images			 6 colors
Belgium 2 images			 3 colors

Table 3 shows a list of 28 distinctive colors by Manufacture country sorted by hue.

Table 3. Extracted distinctive-colors of textile products grouped by manufacture country in the form of color names of Color-definition Space

Hue Name		**Color Name in CIS**
Neutral Colors	4	Black, Dark-gray, Light-Gray, White
Red	3	R/Dull, R/Dark, R/Dark-Grayish
Yellow-Red	6	YR/Grayish, YR/Dark, YR/Dark-Grayish, YR/Very-Pale, YR/Light, YR/Deep
Yellow	3	Y/Strong, Y/Deep, Y/Bright
Green-Yellow	5	GY/Grayish, GY/Dark, GY/Dull, GY/Light, GY/Light-Grayish
Green	1	G/Dull
Blue-Green	0	
Blue	1	B/Light-Grayish
Purple-Blue	1	PB/Light-Grayish
Purple	2	P/Light-Grayish, P/Grayish
Red-Purple	2	RP/Light-Grayish, RP/Grayish

(2) The overview map of image Groups

This section describes how the image information is to be visualized using the distinctive color information obtained by the process of the previous section. By using grouping keys of geographic information, the detailed results of distinctive-color analysis are displayed on the map. At the same time, we show the interface of refinement of group information, such as listing the members of the group and sub-grouping.

Figure 4 shows the results of the distinctive colors extracted from the image group of the manufacture countries. On the right side of the map, the distinctive colors are displayed as features of products manufactured in each country through all the era (16th – 20th century) along with the number of data. On the map of the left side of the interface, representative images of product are shown at the position of the capital of each country. These images are the result of similarity calculation between product images and the distinctive color distribution at the right column.

Figure 4. Geographical visualization of the characteristic of products by manufacture countries

Figure 5 shows that the details of the products are displayed on the right side of the interface if a user selects one representative image of one country on the map.

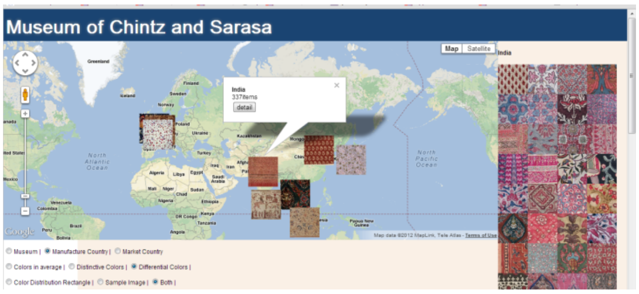


Figure 5. Example of display: details of the product maid in India

Figure 6 shows the different visualization results of analysis by other grouping keys. In this case, the differences of colorization between the Indian textiles exported to the UK and those exported to Japan are displayed. We can recognize the difference at a glance.

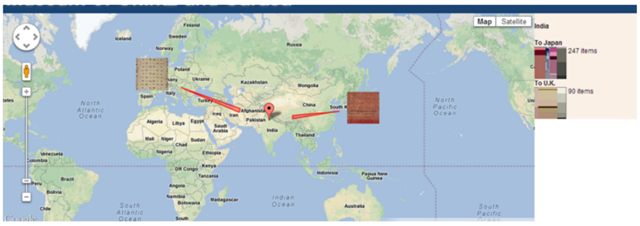


Figure 6. Geographical visualization of the difference between Chintz made in India exported to different countries

Figure 7 is the results using geographical information as grouping key, we can use the era as selection key to view the changes of the colorization of products due to the era.

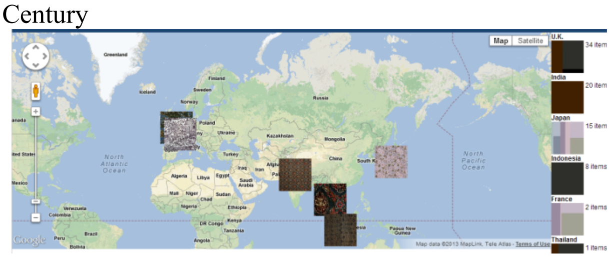
Figure 7 shows an example of time-series visualization of the difference of products made in each manufacture country from 17th Century to 20th Century.

From Figure 7, we can recognize and overview the world trade history from early modern period to the advent of Industrial Revolution, through the development of textile as both manufactured product and cultural property in each country. We can find that the collected items that produced in the 17th-18th century are mainly made in India and exported to other countries (53 items in 17th and 236 items in 18th century). After the period, according to the time series, the products are also being applied to the collection in France, Japan, and Indonesia. In the collection of 20th century, the items that made in the United Kingdom became the majority (67 items). We can also find the change of characteristic colorization such as yellow of French products and grayish and mono-tone colors of products of the United Kingdom.

Textiles grouped by manufacture country in 17th Century

Textiles grouped by manufacture country in 18th Century

Textiles grouped by manufacture country in 19th Century



Textiles grouped by manufacture country in 20th Century

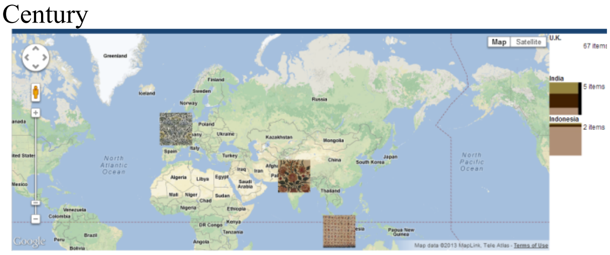


Figure 7. Example of time-series visualization: the difference of products made in each manufacture country from 17th Century to 20th Century.

3.3. The results of rescanning, estimation and comparison with culture-dependent colors for specified colors of Ukiyoe

This section shows the results of estimation with culture-dependent colors in images of Ukiyoe. The color set for rescanning is defined by segmenting RGB into 12 parts for each axis. This set contains 1726 colors. The subset for estimation is constructed from 21 colors in the neighborhood of Strong Red in CIS. The neighborhood distance is one sixth of the distance between pure red and pure white. The color distance is calculated with the CIE2000 formula.

Figure 8 shows the visualization results of rescanning images of Ukiyoe published during the period between Edo era and Meiji era (1864 to 1873). The images are grouped by year. It is said that Strong Red was made by imported aniline dye from the end of Edo period, and was used widely after the Meiji Restoration (1868), when the Meiji Emperor moved from Kyoto to Tokyo.

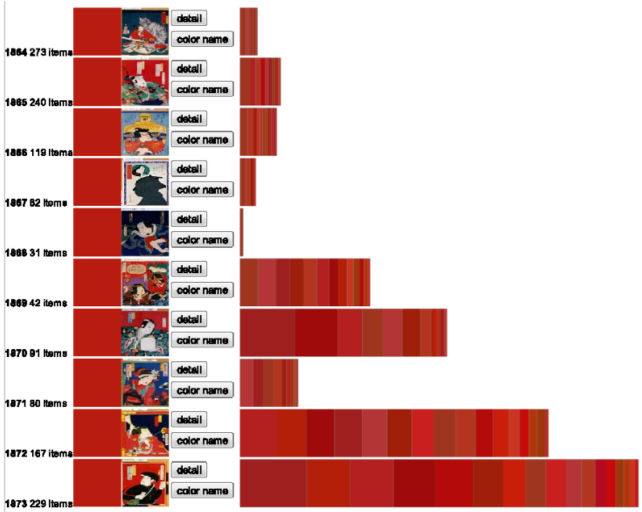


Figure 8. Transition in Strong Red use in Ukiyoe published from 1864 to 1870

Figure 9 shows the estimation results for Strong Red of 7th row of Figure 4 (items published in 1870) with culture-dependent color name. We used Japanese, Chinese, French and European color collections to define culture-dependent colors. The European Traditional Color set (1160 colors) was collected from Nicopon [21]. The other color sets are Chinese (320 colors), French (322 colors), and Japanese (300 colors), as specified in DIC Color Guide [8]. The figure visualize of aggregation of most similar color and similarity for each image. From this result, we can confirm that Strong Red in Ukiyoe published in 1870 is similar to European color name, because aniline dye was imported from Europe.

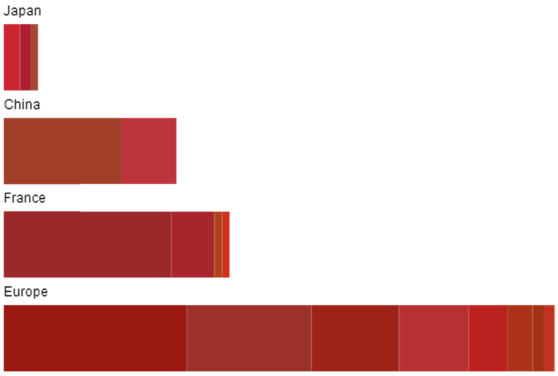


Figure 9. Estimation results for Strong Red in Ukiyoe published in 1870 with culture-dependent colors

Table 4 presents extracted culture-dependent color names for Strong Red in images of Ukiyoe published in 1870.

The value displayed at the left of the color name indicates the number of images which contain the area of the culture-dependent color. The value under the color name indicate amount of similarity between the color distribution in the image and the color name. These color names represent subtle difference.

Table 4. Extracted culture-dependent color names for Strong Red in images of Ukiyoe published in 1870

Japanese		Chinese		French		European	
7	猩々緋 (0.21)	29	血紅 (1.54)	33	rouge sang (2.18)	14	henna (2.39)
7	深緋 (0.14)	15	象牙紅 (0.71)	13	piment (0.56)	14	brick red (1.62)
6	紅樺色 (0.10)			2	tomette (0.11)	9	brazil red (1.15)
				1	coq de roche (0.10)	12	bauk sweet (0.90)
						2	copper red (0.50)
						3	roastbeef (0.34)
						4	derby tan (0.15)
						1	tomato red (0.13)
						1	cardinal red (0.01)

Table 5 shows averaged similarity between Strong Red and estimated culture-dependent color name in Ukiyoe published from 1864 to 1873. An averaged similarity is calculated from aggregated similarity to estimated color with normalization of the image number and the area size used the neighborhood colors of Strong Red. These results indicate the transition of color, not the area size used the specified colors. Red color in Ukiyoe is similar to 紅樺色 in Japanese colors and tometto in French colors before 1870. After 1870, red color in Ukiyoe is similar to 猩々緋 in Japanese colors and henna in French colors. Thus, the system visualizes the subtle difference of specified colors in this way.

Table 5. Transition in averaged similarity between extracted culture-dependent color and Strong Red in Ukiyoe published from 1864 to 1870

year	number of images	Averaged similarity to Japanese color names	Averaged similarity to French color names
1864	273		
1865	240		
1866	119		
1867	62		
1868	31		
1869	42		
1870	91		
1871	80		
1872	167		
1873	229		

4. Conclusion

This paper presents a new art image exploring system. By the experiments, we confirmed that our system enables to extract the characteristic colorization. Our system will lead to a new appreciation environment with dynamic viewpoints and deep analysis of colors.

Reference

[1] Barakbah, A. R. and Kiyoki, Y.: An Emotion-Oriented Image Search System with Cluster based Similarity Measurement using Pillar-Kmeans Algorighm, *Information*

Modelling and Knowledge Bases, IOS Press, XXII, pp.117-136 (2011).
[2] Berlin, B. and Kay, P.: Basic color terms: Their universality and evolution. University of California Pr, (1991).
[3] Birren, F.: Color and human response, *Color Research & Application* 8.2: 75-81 (1983).
[4] Birren, F.: Color: a survey in words and pictures, from ancient mysticism to modern science. Citadel Press (1963).
[5] Chen, X., and Kiyoki, Y.: A visual and semantic image retrieval method based on similarity computing with query-context recognition, Frontiers in Artificial Intelligence and Applications 154: 245 (2007).
[6] Deselaers, T., Keysers, D., & Ney, H.: Features for image retrieval: an experimental comparison, *Information Retrieval* 11.2: 77-107 (2008).
[7] Deselaers, T.: Features for image retrieval, Rheinisch-Westfalische Technische Hochschule, Technical Report, Aachen (2003).
[8] DIC Graphics Corporation: DIC Color Guide,
http://www.dic-graphics.co.jp/en/index.html.
[9] Von Goethe, J. W.: Theory of colours. No. 3. The MIT Press (1840).
[10] Heider, E. R.: Universals in color naming and memory, *Journal of experimental psychology* 93.1: 10 (1972).
[11] Itabashi, Y., Sasaki, S. and Kiyoki, Y.: Cross-cultural Image Computing with Multiple Color-Space Transformation, *Emitter Journal*, Vol.2 No.2, (2012).
[12] Itabashi, Y., Sasaki, S. and Kiyoki, Y.: Distinctive-Color Analytical Visualization for Cross-Cultural Image Computing with 5D World Map, *Proc. Knowledge Creation and Intelligent Computing* (*KCIC 2013*), pp.37-44 (2013).
[13] Kiyoki, Y., Kitagawa, T. and Hayama, T.: A Metadatabase System for Semantic Image Search by a Mathematical Model of Meaning, ACM SIGMOD Record, 23, 4, pp.34-41, (1994).
[14] Kiyoki, Y., Kitagawa, T.: A semantic associative search method for knowledge acquisition, Information Modelling and Knowledge Bases VI, H. Kangassalo et al eds. IOS Press 1995 pp. 121-130, (1995).
[15] Kiyoki, Y., Sasaki, S., Nguyen N. T., Nguyen, T. N. D., Cross-cultural Multimedia Computing with Impression-based Semantic Spaces, Conceptual Modelling and Its Theoretical Foundations, Lecture Notes in Computer Science, Springer, pp.316-328 (2012).
[16] Kherfi, M. L., Ziou, D., and Bernardi, A.: Image retrieval from the world wide web: Issues, techniques, and systems, *ACM Computing Surveys* (*CSUR*) 36.1: 35-67 (2004).
[17] Kobayashi, S, Color Image Scale, Kodansha International (1991).
[18] Luo, M. R., Cui, G., and Rigg, B.: The development of the CIE 2000 colour-difference formula: CIEDE2000, Color Research & Application 26.5: 340-350 (2001).
[19] Nara Blog: http://narablog.com/.
[20] Nguyen, T. N. D., Sasaki, S. and Kiyoki, Y., 5D World PicMap: Imagination-based Image Search System with Spatiotemporal Analyzers, *Proc. IADIS e-Society 2011 Conference*, 8 pages, (2011).
[21] Nicopon: World Traditional Colors, http://www.nicopon.com/iro/yo/.
[22] Niblack, C. W., Barber, R., Equitz, W., et al., QBIC project: querying images by content, using color, texture, and shape, IS&T/SPIE's Symposium on Electronic Imaging: Science and Technology. International Society for Optics and Photonics, (1993).
[23] Sasaki, S., Itabashi, Y., Kiyoki Y. and Chen X.: An Image-Query Creation Method for Representing Impression by Color-based Combination of Multiple Images, Information Modelling and Knowledge Bases, Vol. XX, pp.105-112, (2009).
[24] The Musée de la Toile de Jouy: http://www.museedelatoiledejouy.fr/.
[25] The Smithsonian American Art Museum: http://americanart.si.edu/.
[26] The Tokyo National Museum: http://www.tnm.jp/.
[27] Tokyo Metropolitan Library: http://www.library.metro.tokyo.jp/.
[28] Tufte, E. R.: Envisioning information, Optometry & Vision Science 68.4 (1991): 322-324.
[29] Victoria and Albert Museum: http://www.vam.ac.uk/.
[30] Wang, J., Yang, W. J., and Acharya, R.: Color Space Quantization for Color-Content-Based Query Systems, Multimedia Tools and Applications, 13, 73–91, (2001).