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Visualizing color term differences based on images from the web

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Abstract

Color terms are used to express light spectrum characteristics captured by human vision, and color naming across languages partition color spaces differently. Such partition differences have been surveyed through several empirical experiments that employ Munsell color chips. We propose a novel visualization method for color terms based on thousands of images collected from query results provided by an image search engines such as Google. A series of experiments was conducted using eight basic color terms in seven languages. Pixel values in the images are counted to form color histograms according to the color pallet used in the world color survey. The visualization results can be summarized as follows: (1) Japanese and Korean color terms have wider distributions in the color space than terms in other languages do and (2) color visualizations for color terms pink and brown are affected by their links to proper nouns.

Keywords: Color terms; World color survey; Image search engines; Color visualization

1. Introduction

Color is an important attribute for various fields such as human modeling, user interaction and experience, human factors, and aesthetic design. Product colors often considerably affect on their sales, and the use of appropriate colors in websites is a key to the website's usability. For particular scenarios, colored signs in particular circumstances have extremely high significance, for example, traffic signals on streets and exit signs in buildings. To avoid misunderstanding, these signs are carefully designed with respect to their shapes and colors.

We often refer to colors with words [1]. Color terms such as "red" and "blue" are used to specify characteristics of the light spectrum captured by human vision. It is known that color terms used to map the light spectrum in different languages do not always share the same boundaries in a color space. Such differences in color terms have been investigated through several experiments in which printed color charts are presented to subjects that are native speakers of various languages (for example, the pioneering work of WCS [2] conducted by Berlin and Kay). However, in general, these experiments are generally extremely time-consuming and expensive.

In this paper, we focus on recent advances in digital camera technologies and various web-based services that allow us to collect an enormous number of examples of various images annotated with color terms. The objective of this research is to visualize differences in the links between color terms and actual colors in the images on the Internet. Such image-term pairs can be obtained by querying image search engines and extracting their top results [3]. We visualize pixel color distribution according to the WCS color chip array [4] shown in Fig. 1. We compare eight basic color terms (red, blue, green, yellow, orange, pink, purple, and brown) in seven languages (English, French, German, Russian, Chinese, Japanese, and Korean). The findings based on our visualization results help mutual understanding between different language speakers, which leads to better decision-making for the coloring of products and services for world-wide sales and more secure conveyance of important signs. The use of Internet images allows us to obtain more up-to-date relationships between terms and colors in an extremely inexpensive way compared with conventional methods that use printed color charts.

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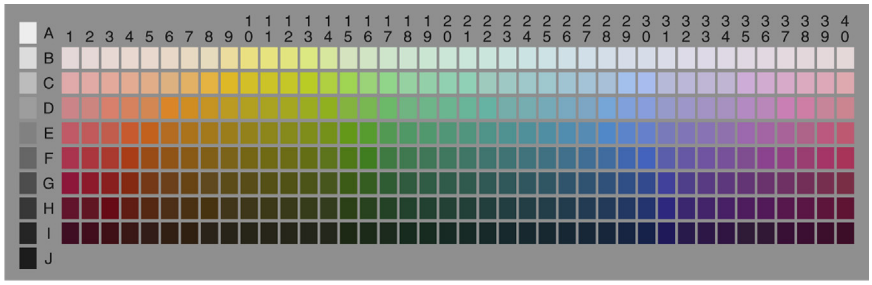

Fig. 1. WCS stimulus pallet [4].

2. Related work

2.1. Human color recognition and its computation models

After the pioneering work World Color Survey (WCS) [2], a large number of studies have been performed to investigate the relationship between color perception and color terms [5–8]. WCS experiments, as well as other succeeding studies, use achromatic colors (gray) with 10 levels and chromatic colors divided into 320 chips shown in Fig. 1. Various language speakers all over the world are presented with some of these 330 (10 + 320) chips in a random order and are asked to identify the color. Their answers about basic color terms in a particular language are collected to form typical boundaries on the 330 color chips (these boundary patterns are called a mode map for that particular language). The investigation on hundreds of languages has shown that many languages share basic boundary patterns in a color space for their color terms. These color-chart-based experiments have been extended to be conducted via Internet by several researchers [9,10]. Automatic color naming methods [11,12], color data sets for that purpose [13], and computational models for color names also have been proposed [14,15]. An automatic determination method has been extended to cover various illumination conditions [16].

2.2. Extraction of latent features from images

Semantic image retrieval algorithms typically process the relationship between pixel color values and color names [12,17,18]. Weijer et al. reported that a color space partition based on actual Internet images improves the accuracy in image recognition and retrieval tasks [19,20]. They collected color component values from images obtained through a Google image search for color name queries. Further, they gathered images on an Internet auction site, eBay, where people attempt to describe their products through words as well as with their photographs. They insisted that employing real images from the Internet archives a better performance than experiments conducted with subjects using printed color charts in a laboratory, which is a very artificial environment compared with real-world usage. Their studies aim to enhance the qualities of image-based applications such as image retrieval and image annotation, by obtaining the color boundaries of English color names from image search results from Google and eBay. This study, on the other hand, examines seven languages (four from Europe and three from east Asia) and aims to study frequency differences between multiple languages in color spaces.

3. Acquiring color distribution from Internet images and its visualization

We acquire pixel color frequencies from Internet images obtained by queries with a set of color terms. Such data acquisition has the following two advantages over conventional color-chart-based methods for color surveys: (1) this approach helps significantly reduce time and costs for the experiments, and (2) a more up-to-date and closer to real-world use of color terms can be achieved. The visualized color frequencies represent the typical usage of color terms by a large number of users in each language.

3.1. Image acquisition

Most search engines offer a function mode to restrict their results within a specified file type or language. Fig. 2 shows such image query examples for the term “blue” in English. By using such a mode, hundreds of links between a particular color term and Internet images relevant to that term can be assembled with almost no cost. Among popular search engines, we use Google as the image source, because it has the largest user share on the Internet.

In the present research, we examine terms related to the following eight colors: red, blue, green, yellow, orange, pink, purple, and brown. These terms are selected from the fundamental ten colors in Japanese and English. Black and white are not in our experiments because they are achromatic and are often used as a default background color in images. 200 images are collected for each of the examined color term in these seven selected languages. A bulk down-loading of hundreds of images in a web page can be performed by an add-on software [21] to Firefox web browser.

We use a hue-saturation diagram shown in Fig. 3. The term “brown” is actually used for colors with lower brightness that cannot be represented on this hue-saturation plane. In Fig. 3, note that there is the absence of a basic term “cyan” opposite to “red”. This is based on the findings in [8,22] and is because this color is often referred to as “light blue” or “light green” in real world usage; further, it does not have its own color category.

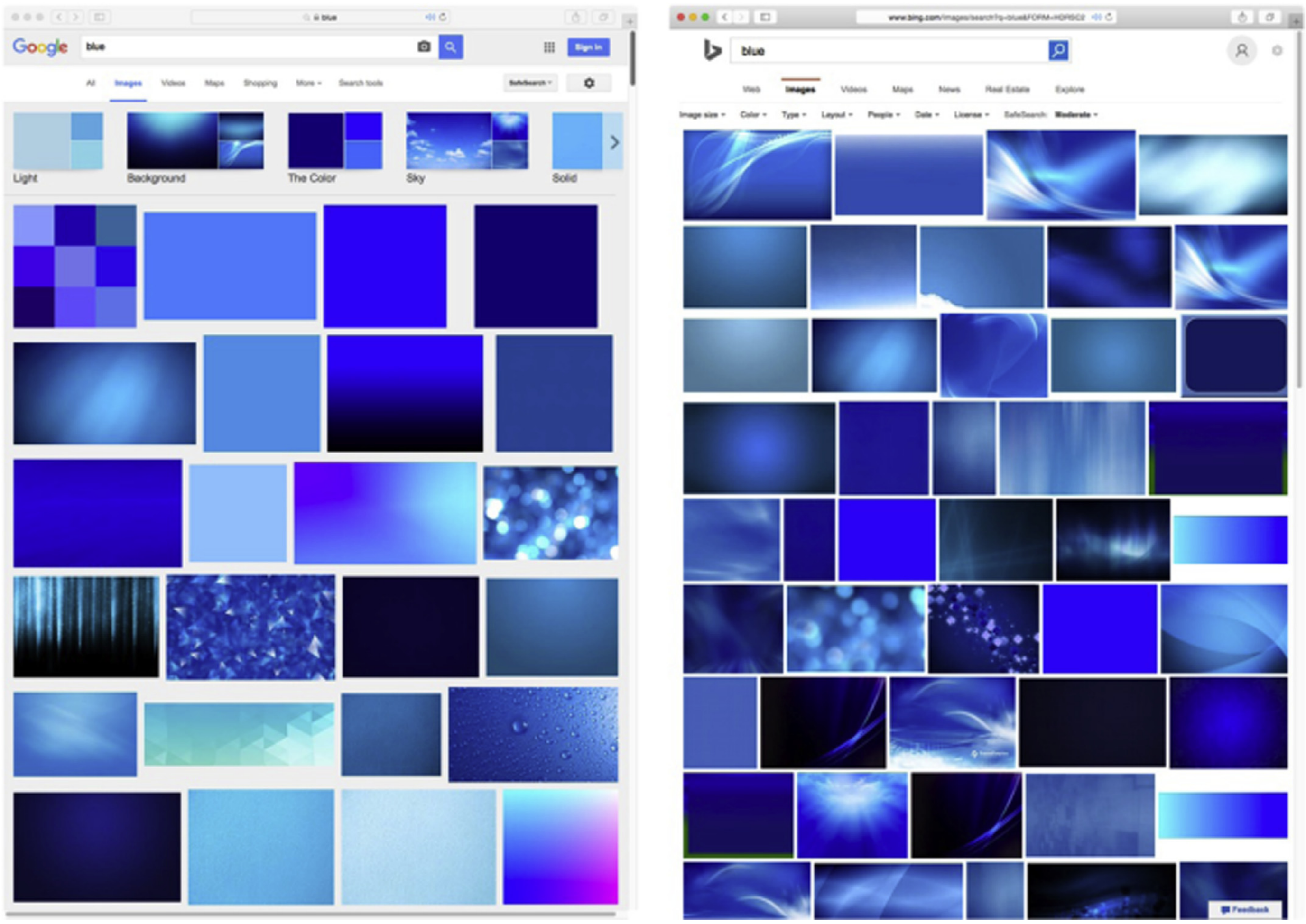

Fig. 2. Results for a query 'blue' from image search engines (left: Google, right: Bing).

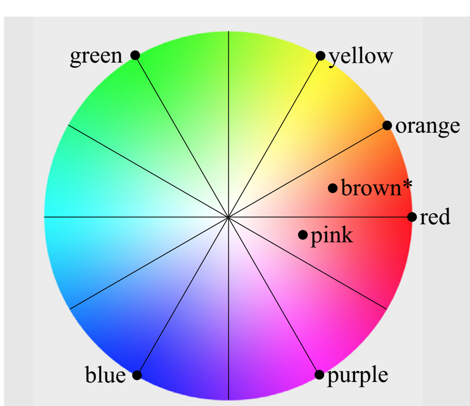

Fig. 3. Eight basic colors selected.

We select four major languages from Europe: English, French, German and Russian, and three languages from East Asia: Chinese, Japanese, and Korean. These seven languages have more than one hundred million native speakers, except for Korean. In our later experiments, we collect $7 \times 8 \times 200 = 11,200$ images in total. The color terms in these languages used for our experiments are shown in Table 1.

Through our preliminary experiments, we found that search results for color terms without the word 'color' in Chinese and Japanese contain too much non-related colors. For example in Japanese, 'brown color' represents brown while 'brown' itself means tea that is green in many cases. These situations could arise because these two languages, and partially Korean, have no word-dividing white space in a sentence, which leads to color-representing letters to appear amid other various words, especially nouns. Family names, location names, company and product names are some of such examples. To reduce such images poorly-related to a particular color term, we add a word meaning 'color' to queries in three Asian languages. Although European languages generally show significant differences between the results with and without the word color, a couple of terms in Western languages, however, show significant differences between with and without 'color' specifications, which is discussed later.

3.2. *Color extraction and visualization*

Next, we count the frequencies of pixel values according to the color pallet used in WCS [2]. The color chip most similar to each pixel in an image is determined in the CIE L*a*b*

Table 1
Eight color terms in seven languages used search engine queries.

	red	blue	green	yellow	pink	brown	orange	purple
English	red	blue	green	yellow	pink	brown	orange	purple
French	rouge	bleu	vert	jaune	rose	brun	orange	violet
German	Rot	Blau	Grün	Gelb	Rosa	Braun	orange	Violett
Russian	красный	синий	зелёный	жёлтый	розовый	коричневый	оранжевый	фиолетовы
Chinese	紅色	藍色	綠色	黃色	粉紅色	褐色	橙色	紫色
Japanese	赤色	青色	緑色	黄色	ピンク色	茶色	オレンジ色	紫色
Korean	빨강색	파랑색	초록색	노랑색	분홍색	갈색	주황색	보라색

Fig. 4. Examples of excluding pixels with the similar colors with image borders.

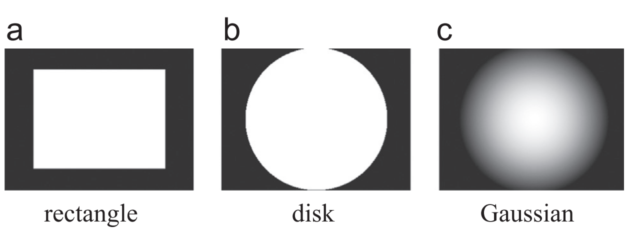

Fig. 5. Weight patterns for counting color frequencies in images: (a) rectangle, (b) disk and (c) Gaussian.

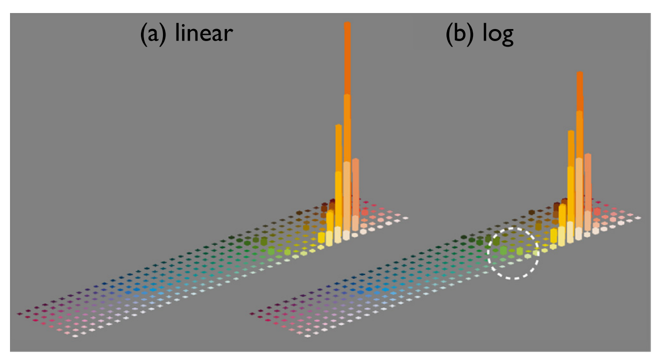

Fig. 6. Visualization example of color distribution for the term 'orange' in English.

color space that is designed to approximate human vision. Assembling all pixels in an image would decrease the accuracy of the extracted colors owing to the less important colors in the surrounding regions of the main object. To avoid such a case, the similar colors with border pixels of images could be excluded for collecting pixel colors (Fig. 4). The surrounding black regions in the figure are extracted as background to be eliminated. We find this approach to be inappropriate for our purpose because the number of eliminated pixels vary significantly with images, and this leads to unstable extraction results. A background removal method such as proposed in [23] can be employed to produce an average location of the object in hundreds of images, which may shape a better weight pattern for counting color frequencies.

In our experiments, we employ three simpler weight patterns for pixel value extraction shown in Fig. 5. The rectangle weight is used to crop an image to be 70% of its original width and height [19]. As a result, this pattern counts values from the center part covering 49% area of the original image. The disk weight is another pattern for objects in the center of the image. Unlike these two weight patterns, the Gaussian distribution has no distinct boundaries of weight values. We report on the results of the comparison of these weight patterns in the experiment section.

Each color term is finally visualized with a three-dimensional histogram with which we can investigate color term characteristics. Fig. 6 shows a visualization example of the term "orange" in English. In our visualization, the heights of the histogram bars represent color frequency values on the logarithm scale. This is because for most terms, these color distributions have a rather strong peak. Such a sharp peak in a

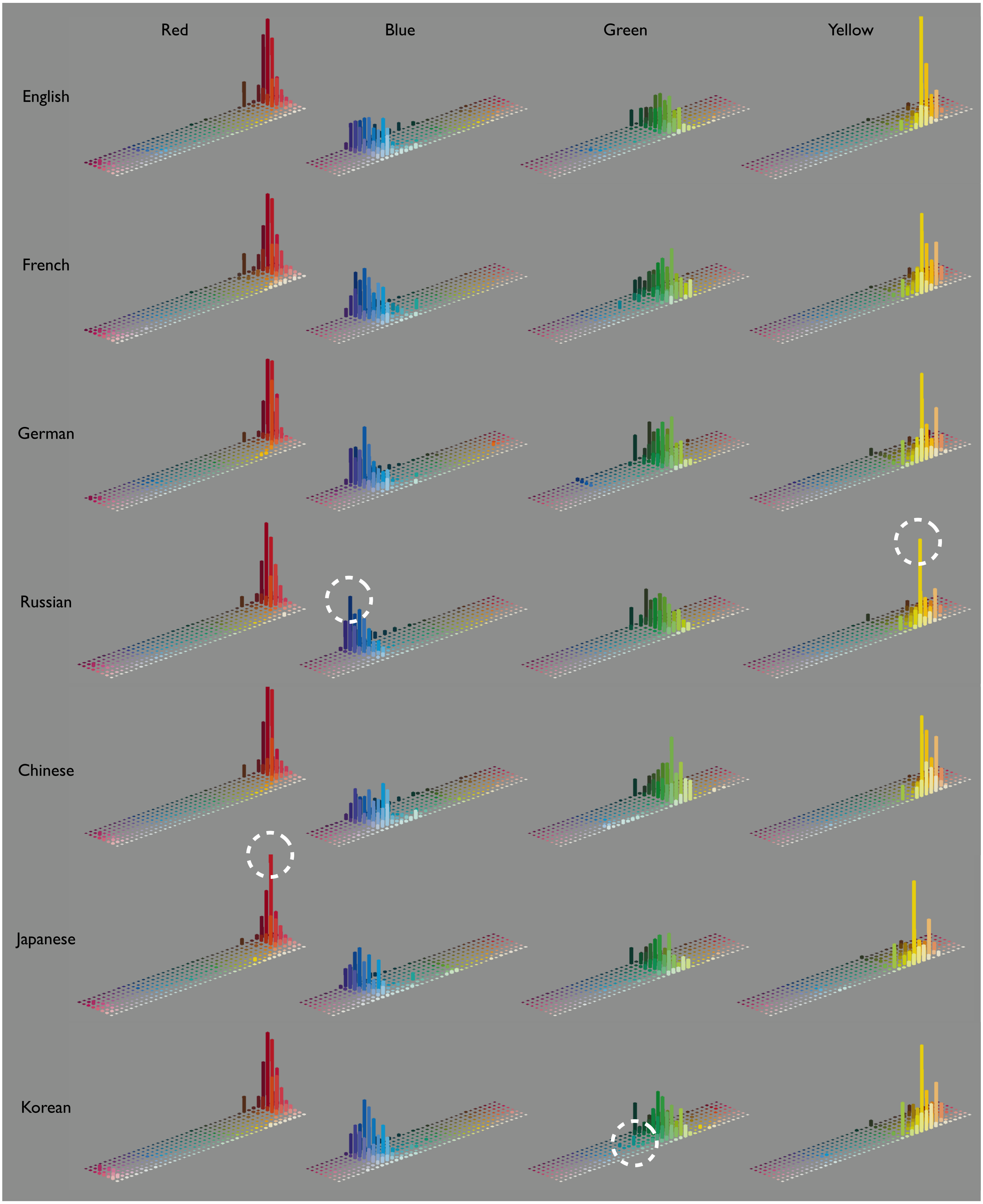

Fig. 7. Color distribution of terms red, blue, green, and yellow in seven languages.

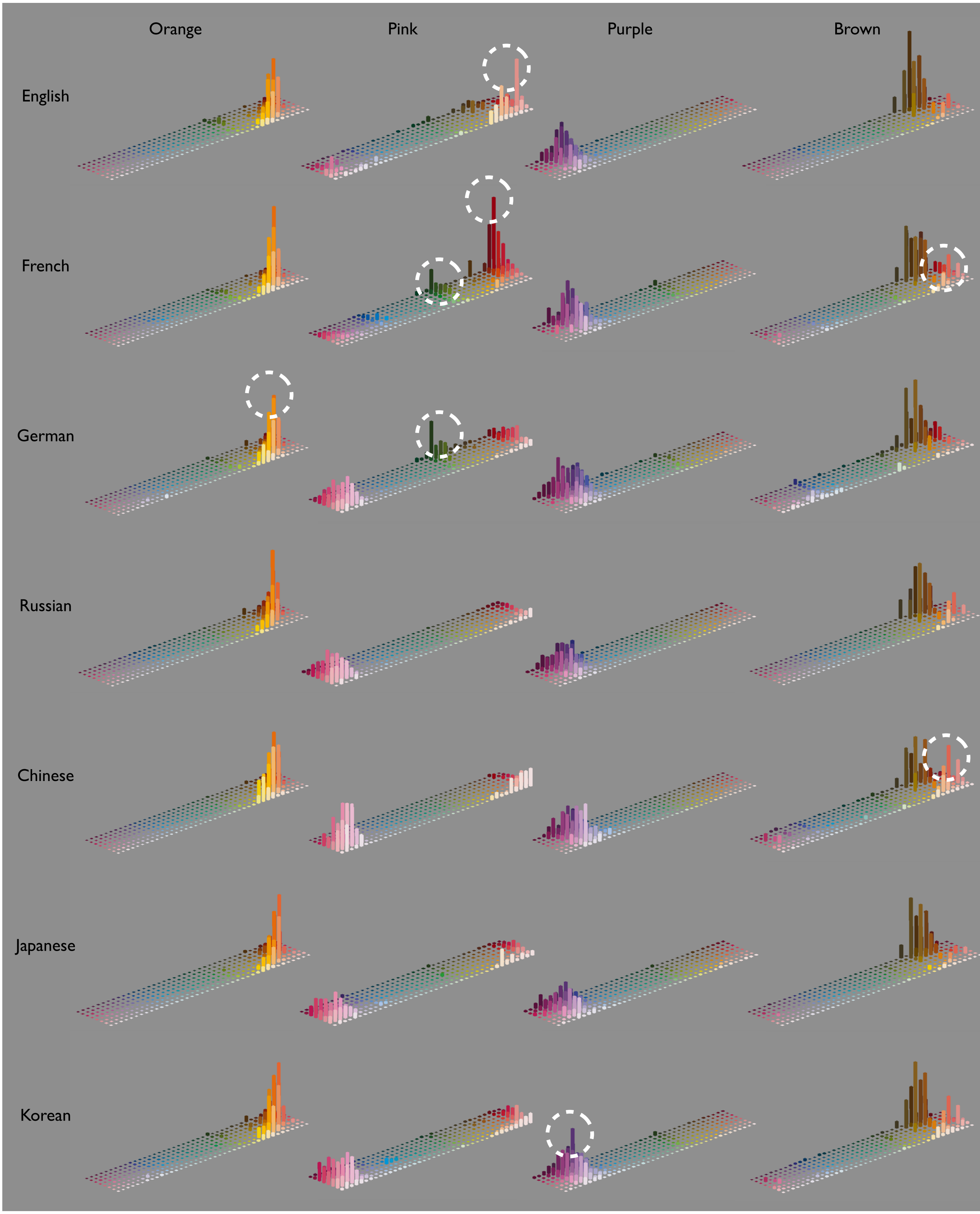

Fig. 8. Color distribution of terms orange, pink, purple, and brown in seven languages.

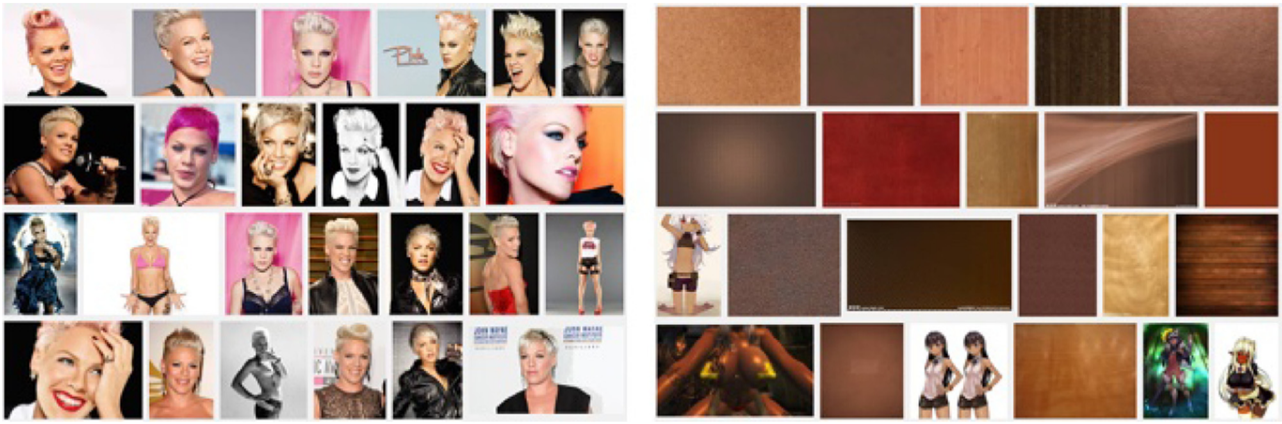

Fig. 9. Examples of color terms used with particular semantics (left: English pink, right: Chinese brown).

linear-scale visualization is often overwhelms other bars in the histogram and makes them difficult to recognize. Both top and micro frequencies with a white circle have better visibility at the same time in (b) logarithmic scale than in (a) the linear scale in the figure.

Our visualization is based on the WCS color pallet in Fig. 1, and its viewing angle is rotated to place a brighter chip foreground for the visibility of three-dimensional histograms.

4. Experimental results

4.1. Color term visualizations

We implemented the proposed approach and conducted the following experiments on iMac Retina (Intel Core i5 3.5 GHz CPU, 8 GB Memory) running Mac OS X. All the images are obtained from the Google website at http://www.google.com. Each color term is queried with our browser configuration in a specific language mode, for example, setting the browser English mode to obtain the image search results for English ‘blue.’ We found slight differences between search results from multiple google domains such as www.google.com, www.google.co.uk, and www.google.co.jp. These minor variations of query result images and their rankings, however, can hardly noticeable in our final visualization of color frequencies. This is the reason for selecting www.google.com, the most popular domain, as our image source. Assembling Internet images for a particular color term in a language and the visualization of their color value frequencies only takes several seconds. The visualization results for the terms red, blue, green, and yellow are shown in Fig. 7. The terms orange, pink, purple, and brown are visualized in Fig. 8. Both figures contain color terms in seven languages from English (top) to Korean (bottom). We found no qualitative differences between the three weight patterns shown in Fig. 5, and selected the simplest rectangle weight pattern for the following visualizations. This selection is also supported by a fact that these three weight patterns produces slight differences in visualization results only if a small number of searched images are fed with (in this case, less than 20 images).

There are several features with white circles that are worth mentioning (Fig. 7):

- Among the results for the term “red” in seven languages, only Japanese has a peak at one chip brighter than the other languages. Color visualizations for the term “red” have generally more compact and similar forms of distribution than other terms.
- Russian language is known to have two types of blue: light and dark [24]. Our visualization correctly suggests that the term used in our experiments corresponds to the darker shade.
- Although the visualizations of the terms for green does not have a significant difference, only the Korean term has small frequencies at light blue chips.
- Russian has a striking peak for yellow color, which is the steepest peak in 56 visualizations.

In addition, Fig. 8 has several points worth mentioning:

- German orange has a slightly brighter peak than other the six languages.
- English, French, and German terms for the color pink have such unique distribution patterns. The English pink is significantly affected by results for a famous woman singer-songwriter, called “Pink” shown in Fig. 9 left. As a result, its color distribution has a large cluster with colors of human skin and hair. French “ *rose*” and German “ *rosa*” are used for representing both pink color and rose flowers. Their visualizations contain small green clusters that are from pixels of rose plant and leaves. The French term “ *rose*” has almost the same distribution pattern as the term “ *rouge*” (red). Pink is the only color in these three Western languages that shows the apparent differences between the results with and without the word ’color’ for the image queries.
- Among seven languages, only Korean has an apparent peak for the term “purple”. The distribution patterns for the color purple, however, are similar for all other languages.
- In the visualization of the terms for brown, French and Chinese have another cluster brighter than brown itself.

Chinese results are affected by skin colors from many cartoon images shown in Fig. 9 right, while the French term is affected by the French family name " *brun*." Note that the German "brown" has a small blue-gray cluster that originates from images of electronics products sold by a German company called "*Braun*."

4.2. Discussions

Fig. 10 shows how each broad term is spread in the WCS color pallet. Those variance values are calculated as squared averages of the distance from the assembled chips to the peak chip in each visualization. This variance equals to zero if all the pixels in an image have only a single color value. We adopted the periodic boundary condition where the left and the right ends are connected to each other in the WCS color pallet (Fig. 1). Large variances are observed for the terms pink, purple, and brown. In Fig. 11, smaller variances of European languages except German are observed, which implies that their color terms are used for more specific colors than other languages in the Internet images.

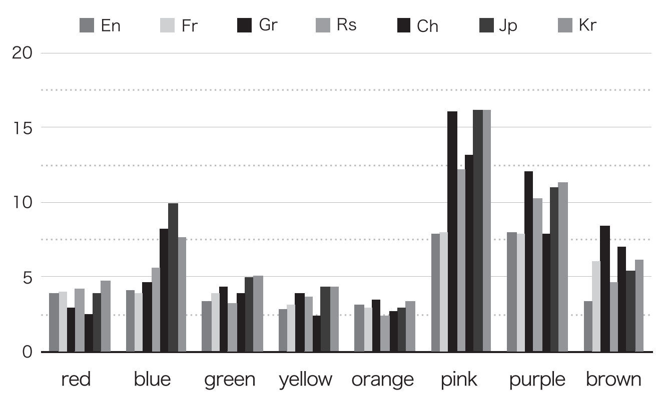

Fig. 10. Color distribution variance of color terms.

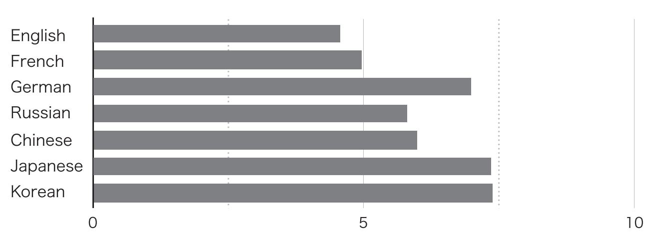

Fig. 11. Color distribution variance of languages.

Our visualization technique relies completely on the output from the search engine we used. In that sense, the relationship that we obtain between color terms and actual colors are seen through the window of the search engine's framework. Each visualization result, however, reflects considerable characteristics of speakers of that language because today's search engines have accumulated a tremendous amount of information about each language and are sufficiently trustable in this regard.

While the visualization results illustrate features of links between color values in the images and color names, those results could also contain some errors due to the method for computing histograms. We investigated the visualizations using the top 20, 50, 100, and 200 images in the image query results. The results for 'red' in English and French are shown in Fig. 12. Except the result obtained using the top 20 images, the visualized histograms have no noticeable difference for different numbers of images used for color frequency counting. This implies that the images in the search results themselves are features of links between colors and color terms, although those result images include minor areas with other colors than the queried color term.

5. Conclusions

We proposed a visualization method for identifying links between color terms in various languages and typical color values used in actual Internet images to investigate their distributions on the WCS color pallet. A series of experiments were conducted using eight basic color terms in four European and three Asian languages. These results indicate that Japanese and Korean color terms often have wider distributions than terms in other languages, and that several color terms are closely linked with proper nouns that do not have a single typical color. These findings can be useful for more efficient

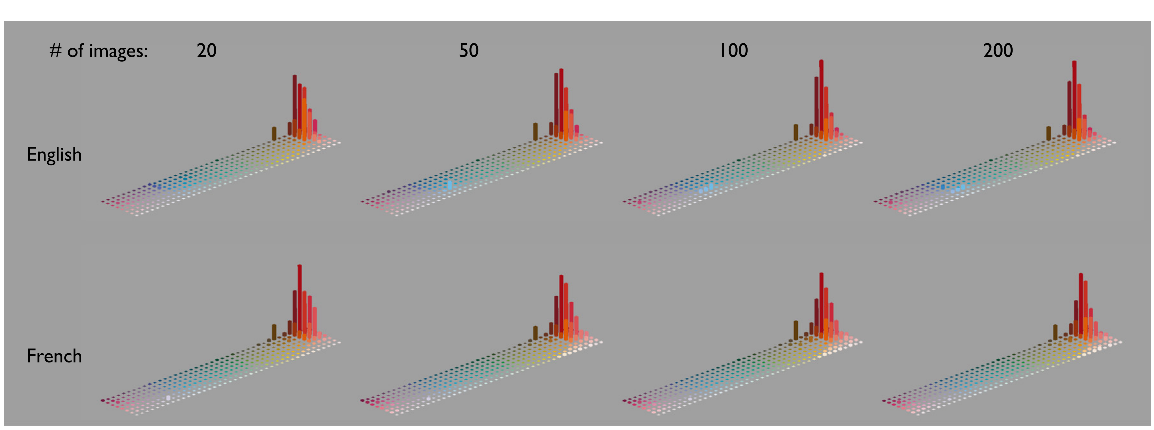

Fig. 12. Color distribution of term 'red' in English and French using 20, 50, 100, and 200 images.

product design and web site navigations addressed for people with various linguistic backgrounds.

Our future work includes the following: color value extraction from each image will be improved to locate salient objects in that image. Other popular languages such as Spanish, Portuguese, Hindi, and Arabic will be included into the investigation. We consider this study to be a very first step to compare color distribution features among various languages to find any primary or language-specific characteristics. The range of terms investigated will extended from color names in this study to various other words such as nouns, verbs and adjectives in future studies, which could help to identify more language-specific topics and materials. One of the purposes of the WCS is to determine category boundaries for color terms in a particular language. The automatic determination of such color boundaries using Internet-collected images is a challenging task, and will be considered in the future scope of this study.

6. Conflict of interest

The authors have no conflict of interest directly relevant to the content of this article.

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