

# Peculiar Image Retrieval by Cross-Language Web-extracted Appearance Descriptions

Shun Hattori

School of Computer Science, Tokyo University of Technology,  
1404-1 Katakura-machi, Hachioji, Tokyo 192-0982, Japan  
*hattori@cs.teu.ac.jp*

**Abstract:** Most researches on Image Retrieval (IR) have aimed at clearing away noisy images and allowing users to retrieve only acceptable images for a target object specified by its object-name. We have become able to get enough acceptable images of a target object just by submitting its object-name as a text-based (keyword-based) query to a conventional Web image search engine such as Google Image Search. However, we can often get only its common images and cannot easily get exhaustive knowledge about its appearance (look and feel), because the retrieval results rarely include its uncommon images. As next steps of IR, it is very important to discriminate between “Typical Images” and “Peculiar Images” in the acceptable images for a target object, and moreover, to collect many different kinds of peculiar images as exhaustively as possible. In other words, “Exhaustiveness” is one of the most important requirements in the next IR for the information-exploding Web. But it is difficult to find clusters which consist of not noisy but peculiar images only by clustering based on image content features. As a solution to the 1st next step, this paper proposes a basic method to more precisely retrieve peculiar images of a target object from the Web by its peculiar appearance descriptions (e.g., color-names) extracted from the Web and/or its peculiar image features (e.g., color-features) converted from them. In addition, this paper also proposes a refined method equipped with cross-language (e.g., translation between Japanese and English) functions and validates its retrieval precision (robustness).

**Keywords:** Image Retrieval, Web Mining, Web Search, Cross-Language, Peculiar Images, Typical Images.

## I. Introduction

In recent years, the Web have had exploding Web images as well as Web documents (text), and various demands have arisen in retrieving Web images as well as Web documents to utilize these information more effectively. When a name of a target object is given by a user, the main goal of conventional keyword-based Web image search engines such as Google Image Search and most researches on Image Retrieval (IR) is to allow the user to clear away noisy images and retrieve only the acceptable images for the target object-name, which just include the target object in their content, as precisely as possible. However, the acceptable images for the quite same object-name are of great variety. For instance, in different shooting environments such as angle, distance, or date, in

different appearance varying among individuals of the same species such as color, shape, or size, with different background or surrounding objects. Therefore, we sometimes want to retrieve not only vague acceptable images of a target object but also its niche images, which meet some kind of additional requirements, i.e., potentially we have various demands in Web image searches. One example of more niche image retrievals, when not only a target object-name and also impression words as additional conditions are given, allows the user to get special images of the target object with the impression [1, 2, 3].

Another example of more niche demands, when only a name of a target object is given, is to retrieve its “Typical Images” [4] which allow us to adequately figure out its typical appearance features and easily associate themselves with the correct object-name, and its “Peculiar Images” [5, 6] which include the target object with not common (or typical) but eccentric (or surprising) appearance features. For instance, most of us would uppermost associate “sunflower” with “yellow one”, “cauliflower” with “white one”, and “tokyo tower” with “red/white one”, while there also exist “red sunflower” or “black one” etc., “purple cauliflower” or “orange one” etc., and “blue tokyo tower” or “green one” etc. When we exhaustively want to know all the appearances of a target object, information about its peculiar appearance features is very important as well as its common ones.

Conventional Web image search engines are mostly Text-Based Image Retrievals (TBIR) by using the filename, alternative text, and surrounding text of each Web image as clues. When such a text-based condition as a name of a target object is given by a user, they give the user the retrieval images which meet the text-based condition. It has become not difficult for us to get typical images as well as acceptable images of a target object just by submitting its object-name to a conventional keyword-based Web image search engine and browsing the top tens of the retrieval results, while peculiar images rarely appear in the top tens of the retrieval results.

The traditional task of IR in the Web is to clear away noisy images and retrieve only acceptable images of a target object from the Web. As next steps of IR in the Web, it is very important to discriminate between “Typical Images” and “Peculiar Images” in the acceptable images, and moreover, to collect many different kinds of peculiar images as exhaustively as possible. In other words, “Exhaustiveness” is one of

the most important requirements in the next-generation Web image retrievals as well as Web document retrievals [7]. As a solution to the 1st next step, this paper proposes a novel method [5, 6] to precisely retrieve peculiar images of a target object whose name is given as a user's original query from the Web, by expanding the original query with its peculiar appearance descriptions (e.g., color-names) extracted from the Web by text mining techniques [8, 9] and/or its peculiar image features (e.g., color-features) converted from the Web-extracted peculiar color-names. To make the basic method more robust, this paper also proposes a refined method [10] equipped with cross-language (e.g., translation between Japanese and English) functions and validates its retrieval precision (robustness).

The remainder of this paper is organized as follows. Section II explains my basic single-language method, and Section III proposes my refined cross-language method to retrieve "Peculiar Images" from the Web. Section IV shows several experimental results to validate my refined cross-language method by comparing with my basic single-language method and such a conventional keyword-based Web image search engine as Google Image Search. Finally, Section V concludes this paper.

## II. Single-Language Peculiar Image Retrieval

This section explains my basic single-language methods [5] for Japanese and [6] for English to precisely search the Web for "Peculiar Images" of a target object whose Japanese/English name is given as a user's original query, by expanding the original query with its peculiar appearance descriptions (e.g., color-names) extracted from the Web by text mining techniques and/or its peculiar image features (e.g., color-features) converted from the Web-extracted peculiar color-names.

Figure 1/2 gives an overview of my basic single-language Peculiar Image Retrieval for English/Japanese object-names that consists of the following four steps, by analyzing not only retrieval-targeted Web image content but also Web document text, when only its object-name is given while its typical/peculiar appearance descriptions/features as additional conditions are not given.

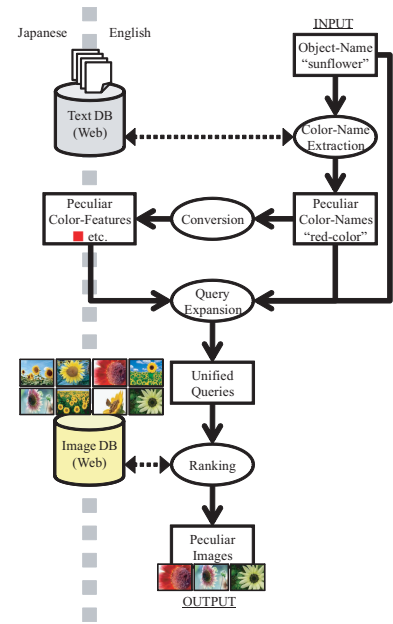
### Step 1. Peculiar Color-Name Extraction from the Web

When a name of a target object as an original query is given by a user, its peculiar color-names (as one kind of appearance descriptions) are extracted from exploding Web documents about the target object by text mining techniques.

The two kinds of lexico-syntactic patterns which consist of a color-name  $cn$  and the English object-name  $on$  are often used as follows:

1. " $cn$ -colored  $on$ ",  
e.g., "yellow-colored sunflower",
2. " $on$  is  $cn$ ",  
e.g., "sunflower is yellow".

Meanwhile, the two kinds of lexico-syntactic patterns which consist of a color-name  $cn$  and the Japanese object-name  $on$  are often used as follows:



**Figure 1:** Single-Language Peculiar Image Retrieval for English target object-names, e.g., "sunflower", to make a domestic trip in only English.

1. " $cn$  色の  $on$ " (iro-no; -colored),  
e.g., "黄色のヒマワリ" (ki-iro-no-himawari; yellow-colored sunflower),
2. " $on$  は  $cn$ " (ha; is),  
e.g., "ヒマワリは黄色" (himawari-ha-ki-iro; sunflower is yellow).

The weight  $pcn(cn, on)$  of Peculiar Color-Name extraction is assigned to each candidate  $cn$  for peculiar color-names of an English object-name  $on$  as follows:

$$pcn(cn, on) := \begin{cases} 0 & \text{if } df(["on \text{ is } cn"]) = 0, \\ \frac{df(["cn\text{-colored } on"])}{df(["on \text{ is } cn"])+1} & \text{otherwise.} \end{cases}$$

where  $df(["q"])$  stands for the frequency of Web documents retrieved by submitting the phrase query  $["q"]$  to Google Web Search. In Japanese:

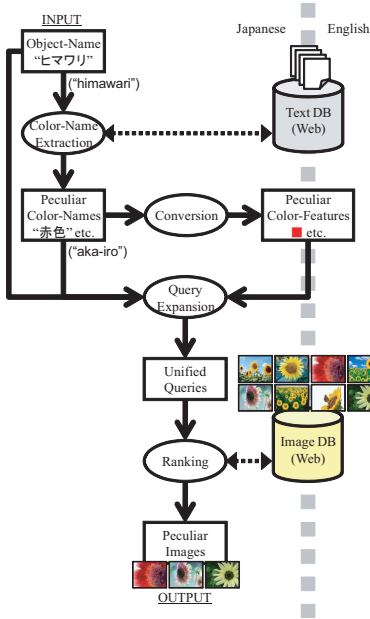
$$pcn(cn, on) := \begin{cases} 0 & \text{if } df(["on \text{ は } cn"]) = 0, \\ \frac{df(["cn\text{色の} on"])}{df(["on \text{ は } cn"])+1} & \text{otherwise.} \end{cases}$$

### Step 2. Conversion from Color-Name to Color-Feature

The peculiar HSV color-features  $cf_p$  (as one kind of image features) of the target object are converted from its Web-extracted peculiar color-names  $cn_p$  by referring the conversion table [11] or [12] in each language.

### Step 3. Query Expansion by Color-Name/Feature

Here, we have three kinds of clues to retrieve peculiar images from the Web: not only a target object-name  $on$  (text-based condition) as an original query given by a user, but also its peculiar color-names  $cn_p$  (text-based condition) extracted from Web documents in the Step 1, and its peculiar color-features  $cf_p$  (content-based condition) converted from its peculiar color-names in the Step 2.



**Figure. 2:** Single-Language Peculiar Image Retrieval for Japanese target object-names, e.g., “ヒマワリ” (himawari; sunflower), to make a domestic trip in only Japanese.

The original query ( $q_0 = \text{text: ["on"]} \text{ AND content: null}$ ) can be expanded by its peculiar color-names  $cn_p$  and/or its peculiar color-features  $cf_p$  as follows:

$$q_1 = \text{text: ["on"]} \text{ AND content: } cf_p,$$

$$q_2 = \text{text: ["} cn_p\text{-colored on"]} \text{ OR ["} cn_p \text{ 色の on"]} \text{ AND content: null,}$$

$$q_3 = \text{text: ["} cn_p\text{-colored on"]} \text{ OR ["} cn_p \text{ 色の on"]} \text{ AND content: } cf_p.$$

#### Step 4. Image Ranking by Expanded Queries

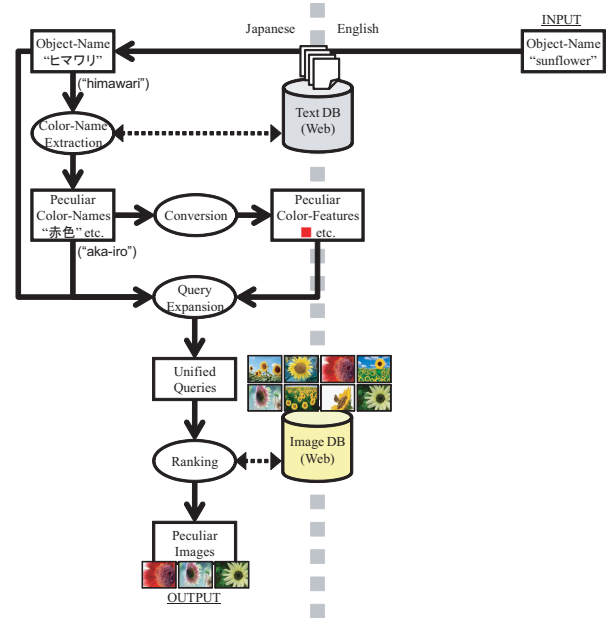
First, the weight  $\text{pir}_{q_1}(i, on)$  of Peculiar Image Retrieval based on the 1st type of expanded query ( $q_1 = \text{text: ["on"]} \text{ AND content: } cf_p$ ) is assigned to a Web image  $i$  in image database(s) for a target object-name  $on$  and is defined as

$$\text{pir}_{q_1}(i, on) := \max_{\forall (cn_p, cf_p)} \left\{ \text{pcn}(cn_p, on) \cdot \text{cont}(i, cf_p) \right\},$$

$$\text{cont}(i, cf_p) := \sum_{\forall cf} \text{sim}(cf, cf_p) \cdot \text{prop}(cf, i),$$

where a Web image  $i$  is retrieved by submitting the text-based query ["on"] (e.g., ["sunflower"]) to Google Image Search,  $\forall (cn_p, cf_p)$  stands for not completely any pair but each pair of its Web-extracted peculiar color-name  $cn_p$  and its converted peculiar color-feature  $cf_p$  in the Step 2. In addition,  $\text{cont}(i, cf_p)$  stands for how much the Web image  $i$  contains the color-feature  $cf_p$  and its similar color-features,  $\text{sim}(cf, cf_p)$  stands for the similarity between color-features  $cf$  and  $cf_p$  in the HSV (Hue-Saturation-Value/Brightness) color space [13], and  $\text{prop}(cf, i)$  stands for the proportion of the color-feature  $cf$  in the Web image  $i$ .

Next, the peculiarity  $\text{pir}_{q_2}(i, on)$  of a Web image  $i$  in image database(s) for a target object-name  $on$  based on the 2nd



**Figure. 3:** Cross-Language Peculiar Image Retrieval for English target object-names, e.g., “sunflower”, to make a one-way trip in English → Japanese.

type of expanded query ( $q_2 = \text{text: ["} cn_p\text{-colored on"]} \text{ OR ["} cn_p \text{ 色の on"]} \text{ AND content: null}$ ) is defined as

$$\text{pir}_{q_2}(i, on) := \max_{\forall cn_p} \left\{ \frac{\text{pcn}(cn_p, on)}{\text{rank}(i, on, cn_p)^2} \right\},$$

where  $\forall cn_p$  stands for not completely any color-name but each Web-extracted peculiar color-name  $cn_p$  in the Step 1, and  $\text{rank}(i, on, cn_p)$  stands for the rank of a Web image  $i$  in the retrieval results by submitting the text-based query [" $cn_p$ -colored on"] in English or [" $cn_p$  色の on"] in Japanese to Google Image Search.

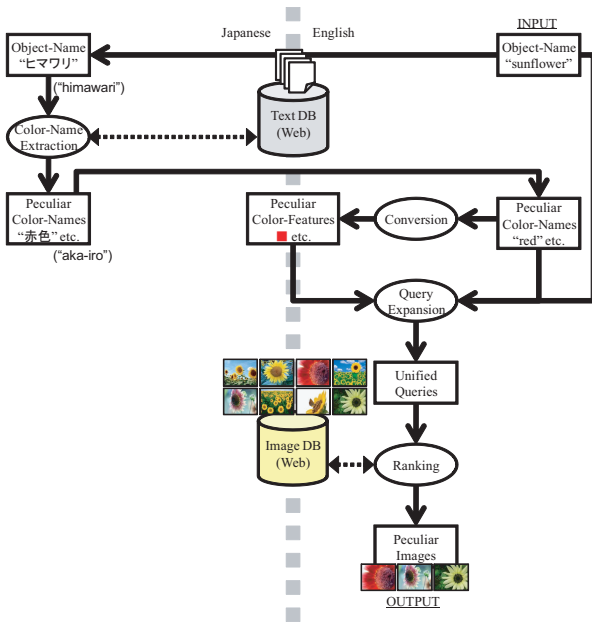
Last, the peculiarity  $\text{pir}_{q_3}(i, on)$  of a Web image  $i$  in image database(s) for a target object-name  $on$  based on the 3rd type of expanded query ( $q_3 = \text{text: ["} cn_p\text{-colored on"]} \text{ OR ["} cn_p \text{ 色の on"]} \text{ AND content: } cf_p$ ) is defined as

$$\text{pir}_{q_3}(i, on) := \max_{\forall (cn_p, cf_p)} \left\{ \frac{\text{pcn}(cn_p, on) \cdot \text{cont}(i, cf_p)}{\text{rank}(i, on, cn_p)} \right\},$$

where  $\forall (cn_p, cf_p)$  stands for not completely any pair but each pair of its Web-extracted peculiar color-name  $cn_p$  and its converted peculiar color-feature  $cf_p$ .

### III. Cross-Language Peculiar Image Retrieval

This section proposes a refined method [10] equipped with cross-language (translation between Japanese and English) functions to make the basic single-language method more robust. Figure 3 and 4 show my refined cross-language Peculiar Image Retrievals for English target object-names. My previous single-language method in Figure 1 runs in only English language space, while my refined cross-language methods run in Japanese language space as well as English one. When an English target object-name  $on_e$  is given by a user, my refined cross-language method in Figure 3 runs from English to Japanese language space as follows:



**Figure 4:** Cross-Language Peculiar Image Retrieval for English target object-names, e.g., “sunflower”, to make a round trip in English → Japanese → English.

**Step 0.** translates the English target object-name  $on_e$ , e.g., “sunflower”, into its Japanese object-name  $on_j$ , e.g., “ヒマワリ” (himawari; sunflower), by using cross-language (automatic translation from English to Japanese) functions,

**Step 1.** extracts its Japanese peculiar color-names  $cn_j$ , e.g., “赤色” (aka-iro; red) and “白色” (shiro-iro; white), of its translated Japanese object-name  $on_j$  from the Web by using the two kinds of Japanese lexico-syntactic patterns and the weight  $pcn(cn_j, on_j)$  in Step 1 of Sec. II,

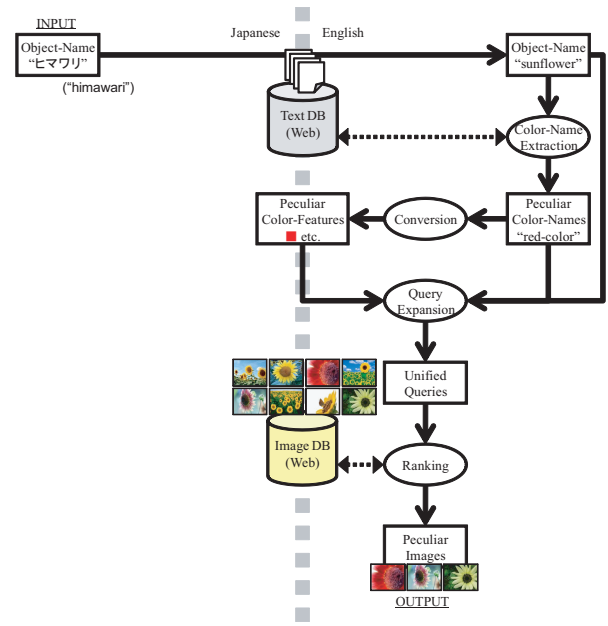
**Step 2.** converts its Web-extracted Japanese peculiar color-names  $cn_j$ , e.g., “赤色” (aka-iro; red) and “白色” (shiro-iro; white), into its peculiar color-features  $cf_j$ , e.g., ■:red and □:white, by referring the Japanese conversion table [11] in the Step 2 of Section II,

**Step 3-4.** retrieves its peculiar images from Web image database(s) by its translated Japanese object-name  $on_j$ , its Web-extracted Japanese peculiar color-names  $cn_j$ , and/or its converted peculiar color-features  $cf_j$ .

Meanwhile, my refined cross-language method in Figure 4 runs back and forth between English and Japanese language spaces as follows:

**Step 0.** translates its target English object-name  $on_e$ , e.g., “sunflower”, into its Japanese object-name  $on_j$ , e.g., “ヒマワリ” (himawari; sunflower), by using cross-language (automatic translation from English to Japanese) functions,

**Step 1.** extracts its Japanese peculiar color-names  $cn_j$ , e.g., “赤色” (aka-iro; red) and “白色” (shiro-iro; white), of its translated Japanese object-name  $on_j$  from the Web by using the two kinds of Japanese lexico-syntactic patterns and the weight  $pcn(cn_j, on_j)$  in the Step 1 of



**Figure 5:** Cross-Language Peculiar Image Retrieval for Japanese target object-names, e.g., “ヒマワリ” (himawari; sunflower), to make a one-way trip in Japanese → English.

Section II, and translates its Japanese peculiar color-names  $cn_j$  into its English peculiar color-names  $cn_e$ , e.g., “red” and “white”, by using cross-language (automatic translation from Japanese to English) functions,

**Step 2.** converts its Web-extracted-and-translated English peculiar color-names  $cn_e$ , e.g., “red” and “white”, into its peculiar color-features  $cf_e$ , e.g., ■:red and □:white, by referring the English conversion table [12],

**Step 3-4.** retrieves its peculiar images from Web image database(s) by its target English object-name  $on_e$ , its Web-extracted-and-translated English peculiar color-names  $cn_e$ , and/or its converted peculiar color-features  $cf_e$  in the Steps 3-4 of Section II.

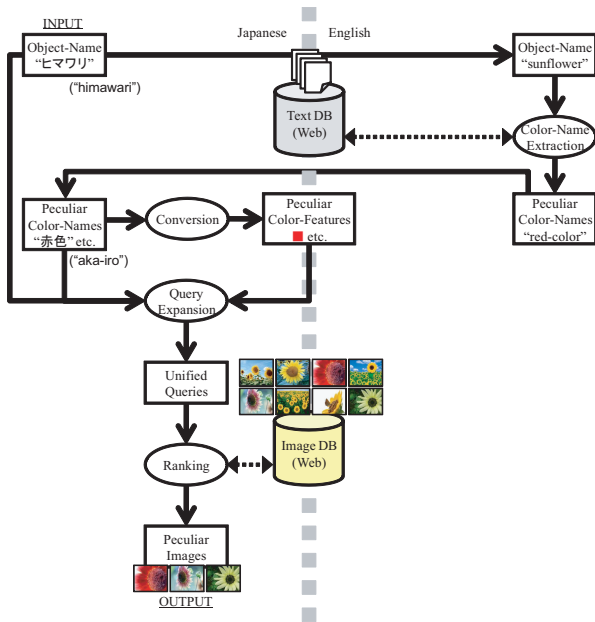
Figure 5 and 6 show my refined cross-language Peculiar Image Retrievals for Japanese target object-names. My previous single-language method in Figure 2 runs in only Japanese language space, while my refined cross-language methods run in English language space as well as Japanese one.

When a Japanese target object-name  $on_j$  is given by a user, my refined cross-language method in Figure 5 runs from Japanese to English language space as follows:

**Step 0.** translates the Japanese target object-name  $on_j$ , e.g., “ヒマワリ” (himawari; sunflower), into its English object-name  $on_e$ , e.g., “sunflower”, by using cross-language (automatic translation from Japanese to English) functions,

**Step 1.** extracts its English peculiar color-names  $cn_e$ , e.g., “red-color” and “white-color”, of its translated English object-name  $on_e$  from the Web by using the two kinds of English lexico-syntactic patterns and the weight  $pcn(cn_e, on_e)$  in the Step 1 of Section II,

**Step 2.** converts its Web-extracted English peculiar color-names  $cn_e$ , “red-color” and “white-color”, into its pe-



**Figure 6:** Cross-Language Peculiar Image Retrieval for Japanese target object-names, e.g., “ヒマワリ” (himawari), to make a round trip in Japanese → English → Japanese.

cular color-features  $cf_e$ , e.g., ■:red and □:white), by referring the English conversion table [12],

**Step 3-4.** retrieves its peculiar images from Web image database(s) by its translated English object-name  $on_e$  and its Web-extracted peculiar color-names  $cn_e$  and/or its converted peculiar color-features  $cf_e$ .

Meanwhile, my refined cross-language method in Figure 6 runs back and forth between Japanese and English language spaces as follows:

**Step 0.** translates the Japanese target object-name  $on_j$ , e.g., “ヒマワリ” (himawari; sunflower), into its English object-name  $on_e$ , e.g., “sunflower”, by using cross-language (automatic translation from Japanese to English) functions,

**Step 1.** extracts its English peculiar color-names  $cn_e$ , e.g., “red-color” and “white-color”, of its translated English object-name  $on_e$  from the Web by using the two kinds of English lexico-syntactic patterns and the weight  $pcn(cn_e, on_e)$ , and translates its English peculiar color-names  $cn_e$  into its Japanese peculiar color-names  $cn_j$ , e.g., “赤色” (aka-iro; red) and “白色” (shiro-iro; white), by using cross-language (automatic translation from English to Japanese) functions,

**Step 2.** converts its Web-extracted-and-translated Japanese peculiar color-names  $cn_j$ , e.g., “赤色” (aka-iro; red) and “白色” (shiro-iro; white), into its peculiar color-features  $cf_j$ , e.g., ■:red and □:white), by referring the Japanese conversion table [11] in the Step 2 of Section II,

**Step 3-4.** retrieves its peculiar images from Web image database(s) by its target Japanese object-name  $on_j$  and its Web-extracted-and-translated Japanese peculiar color-names  $cn_j$  and/or its converted peculiar color-features  $cf_j$  in the Steps 3-4 of Section II.

## IV. Experiment

This section shows several experimental results for the following eight kinds of English/Japanese target object-names from among four categories to validate my refined cross-language methods to retrieve their “Peculiar Images” from the Web by comparing with my previous single-language method and such a conventional keyword-based Web image search engine as Google Image Search.

### 1. Plants:

- “sunflower” and “ヒマワリ” (himawari) whose typical color is yellow,
- “cauliflower” and “カリフラワー” (karihurawā) whose typical color is white,

### 2. Landmarks:

- “tokyo tower” and “東京タワー” (tōkyō-tawā) whose typical color is red (international-orange),
- “nagoya castle” and “名古屋城” (nagoya-jō) whose typical color is white,

### 3. Animals:

- “praying mantis” and “カマキリ” (kamakiri) whose typical color is green,
- “cockroach” and “ゴキブリ” (gokiburi) whose typical color is brown,

### 4. Others:

- “wii” in both languages whose typical color is white,
- “sapphire” and “サファイア” (safaia) whose typical color is blue.

Table 1 shows each precision for the eight English target object-names and the average precision of the top 20 and top 100 peculiar images retrieved by my refined cross-language Peculiar Image Retrieval (method: EJ\*q1-3 and EJE\*q1-3), my basic single-language Peculiar Image Retrieval (method: E\*q1-3), and Google Image Search (E\*q0) as a conventional keyword-based Web image search engine. The values listed in boldface are the best in each target object-name or the average. It shows that my refined cross-language EJE\*q2 method based on the 2nd type of expanded query ( $q2 = \text{text:} [ "cn_p\text{-colored } on_e ] \text{ AND content: null}$ ) to make a round trip in English → Japanese → English as shown in Figure 4 gives the best performance, and my cross-language EJE\*q3 method based on the 3rd type of expanded query ( $q3 = \text{text:} [ "cn_p\text{-colored } on_e ] \text{ AND content: } cf_p$ ) to make a round trip gains the second-best. Note that my EJ\*qX methods are superior for only “nagoya castle”. Figures 7 and 8 show the top  $k$  average precision of my refined cross-language methods, my basic single-language methods, and Google Image Search. They also show that my cross-language EJE\*q2 method is superior to all the others, and that my cross-language EJE\*qX methods to make a round trip from English to Japanese are the best, my cross-language EJ\*qX methods to go from English to Japanese (and not to come back) are the second-best (better), and my basic single-language E\*qX methods are worse.

Table 1: Cross-Language effects on top 20 &amp; 100 precision of Peculiar Image Retrievals for English object-names.

		E		EJ		EJE	
		only English		English → Japanese		English → Japanese → English	
q0	sunflower	0/20	2/100				
	cauliflower	6/20	40/100				
	tokyo tower	0/20	7/100				
	nagoya castle	0/20	1/100				
	praying mantis	1/20	4/100				
	cockroach	6/20	14/100				
	wii	5/20	17/100				
	sapphire	3/20	8/100				
	(avg.)	2.6/20	11.6/100				
q1	sunflower	1/20	2/100	1/20	9/100	0/20	2/100
	cauliflower	2/20	40/100	8/20	40/100	0/20	40/100
	tokyo tower	0/20	7/100	5/20	12/100	3/20	7/100
	nagoya castle	0/20	1/100	0/20	0/100	0/20	1/100
	praying mantis	2/20	4/100	2/20	8/100	0/20	4/100
	cockroach	3/20	14/100	3/20	23/100	0/20	14/100
	wii	0/20	17/100	5/20	13/100	6/20	17/100
	sapphire	5/20	8/100	9/20	40/100	4/20	8/100
	(avg.)	1.6/20	11.6/100	4.1/20	18.1/100	1.6/20	11.6/100
q2	sunflower	11/20	37/100	9/20	<b>54</b> /100	6/20	29/100
	cauliflower	5/20	20/100	14/20	61/100	14/20	<b>62</b> /100
	tokyo tower	0/20	0/100	9/20	40/100	<b>13</b> /20	<b>43</b> /100
	nagoya castle	0/20	0/100	<b>4</b> /20	7/100	0/20	0/100
	praying mantis	2/20	3/100	6/20	15/100	<b>9</b> /20	<b>24</b> /100
	cockroach	0/20	0/100	8/20	12/100	<b>12</b> /20	<b>43</b> /100
	wii	5/20	18/100	2/20	11/100	<b>16</b> /20	61/100
	sapphire	13/20	48/100	11/20	66/100	18/20	<b>81</b> /100
	(avg.)	4.5/20	15.8/100	7.9/20	33.2/100	<b>11.0</b> /20	<b>42.9</b> /100
q3	sunflower	7/20	36/100	<b>12</b> /20	50/100	2/20	18/100
	cauliflower	5/20	13/100	13/20	51/100	<b>16</b> /20	48/100
	tokyo tower	0/20	0/100	1/20	29/100	7/20	20/100
	nagoya castle	0/20	0/100	<b>4</b> /20	6/100	0/20	0/100
	praying mantis	2/20	3/100	3/20	6/100	3/20	14/100
	cockroach	0/20	0/100	4/20	11/100	7/20	26/100
	wii	9/20	44/100	4/20	5/100	<b>16</b> /20	<b>72</b> /100
	sapphire	14/20	62/100	16/20	64/100	<b>20</b> /20	79/100
	(avg.)	4.6/20	19.8/100	7.1/20	27.8/100	8.9/20	34.6/100

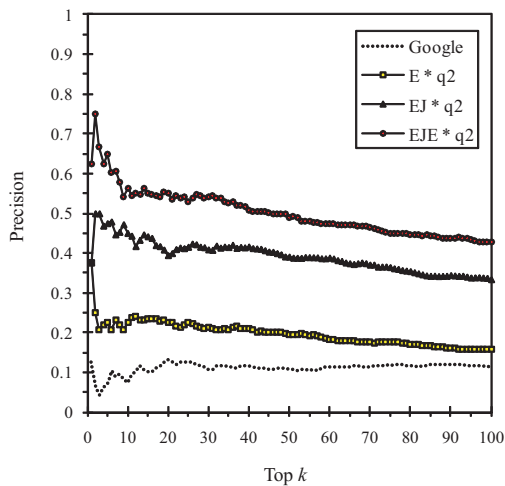
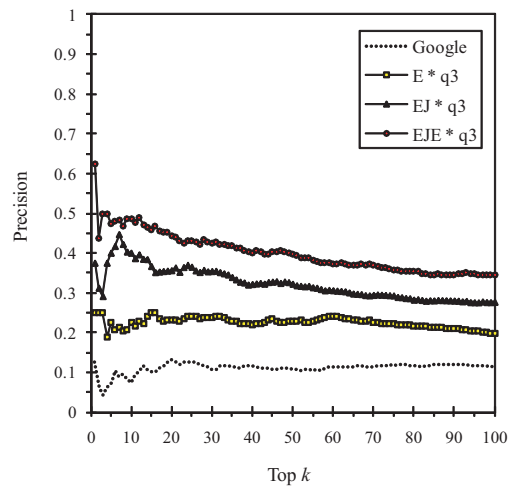
Figure 7: Top  $k$  average precision of Google Image Search vs. Peculiar Image Retrievals (method: X\*q2) for English object-names.Figure 8: Top  $k$  average precision of Google Image Search vs. Peculiar Image Retrievals (method: X\*q3) for English object-names.

Table 2: Cross-Language effects on top 20 & 100 precision of Peculiar Image Retrievals for Japanese object-names.

		J only Japanese		JE Japanese → English		JEJ Jap. → Eng. → Jap.	
q0 Google Image	ヒマワリ (himawari; sunflower)	0/20	9/100				
	カリフラワー (karihurawā; cauliflower)	9/20	40/100				
	東京タワー (tōkyō-tawā; tokyo tower)	0/20	12/100				
	名古屋城 (nagoya-jō; nagoya castle)	0/20	0/100				
	カマキリ (kamakiri; praying mantis)	1/20	8/100				
	ゴキブリ (gokiburi; cockroach)	7/20	<b>23</b> /100				
	wii	4/20	13/100				
	サファイア (safaia; sapphire)	4/20	40/100				
	(Avg.)	3.1/20	18.1/100				
	q1	ヒマワリ (himawari; sunflower)	1/20	9/100	1/20	2/100	2/20
カリフラワー (karihurawā; cauliflower)		8/20	40/100	2/20	40/100	6/20	41/100
東京タワー (tōkyō-tawā; tokyo tower)		5/20	12/100	0/20	7/100	1/20	12/100
名古屋城 (nagoya-jō; nagoya castle)		0/20	0/100	0/20	0/100	0/20	0/100
カマキリ (kamakiri; praying mantis)		2/20	8/100	2/20	4/100	2/20	8/100
ゴキブリ (gokiburi; cockroach)		3/20	<b>23</b> /100	3/20	14/100	4/20	<b>23</b> /100
wii		5/20	13/100	0/20	17/100	1/20	13/100
サファイア (safaia; sapphire)		9/20	40/100	5/20	8/100	8/20	40/100
(avg.)		4.1/20	18.1/100	1.6/20	11.5/100	3.0/20	18.3/100
q2		ヒマワリ (himawari; sunflower)	9/20	<b>54</b> /100	11/20	37/100	13/20
	カリフラワー (karihurawā; cauliflower)	<b>14</b> /20	<b>61</b> /100	5/20	20/100	12/20	53/100
	東京タワー (tōkyō-tawā; tokyo tower)	<b>9</b> /20	40/100	0/20	0/100	7/20	<b>45</b> /100
	名古屋城 (nagoya-jō; nagoya castle)	4/20	7/100	0/20	0/100	0/20	0/100
	カマキリ (kamakiri; praying mantis)	<b>6</b> /20	15/100	2/20	3/100	6/20	23/100
	ゴキブリ (gokiburi; cockroach)	<b>8</b> /20	12/100	0/20	0/100	3/20	11/100
	wii	2/20	11/100	5/20	18/100	4/20	15/100
	サファイア (safaia; sapphire)	11/20	66/100	13/20	48/100	14/20	59/100
	(avg.)	7.9/20	<b>33.3</b> /100	4.5/20	15.8/100	7.4/20	31.6/100
	q3	ヒマワリ (himawari; sunflower)	12/20	50/100	7/20	36/100	<b>14</b> /20
カリフラワー (karihurawā; cauliflower)		13/20	51/100	5/20	13/100	9/20	29/100
東京タワー (tōkyō-tawā; tokyo tower)		1/20	29/100	0/20	0/100	5/20	39/100
名古屋城 (nagoya-jō; nagoya castle)		<b>4</b> /20	6/100	0/20	0/100	0/20	0/100
カマキリ (kamakiri; praying mantis)		3/20	<b>6</b> /100	2/20	3/100	<b>6</b> /20	<b>25</b> /100
ゴキブリ (gokiburi; cockroach)		4/20	11/100	0/20	0/100	4/20	11/100
wii		4/20	5/100	<b>9</b> /20	<b>44</b> /100	<b>9</b> /20	14/100
サファイア (safaia; sapphire)		16/20	64/100	14/20	62/100	<b>17</b> /20	<b>69</b> /100
(avg.)		7.1/20	27.8/100	4.6/20	19.8/100	<b>8.0</b> /20	28.8/100

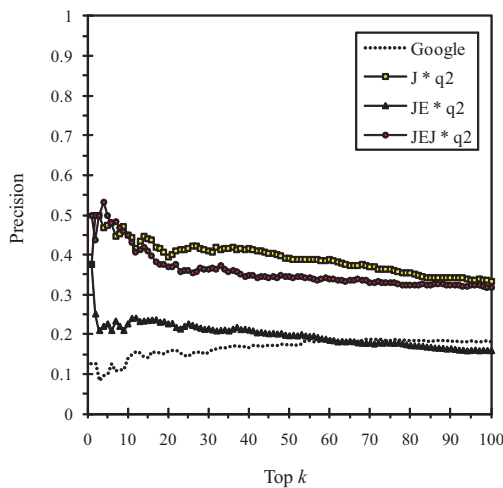


Figure 9: Top  $k$  average precision of Google Image Search vs. Peculiar Image Retrievals (method: X\*q2) for Japanese object-names.

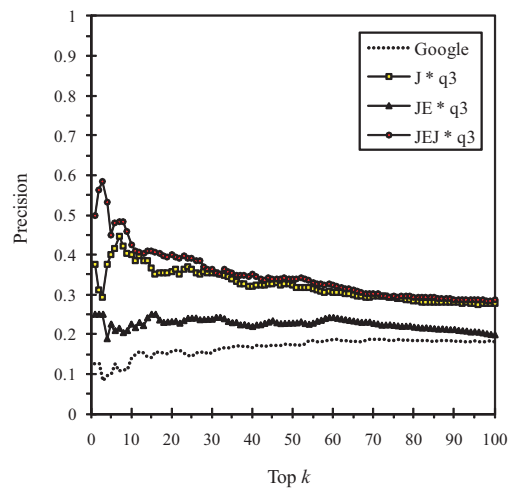


Figure 10: Top  $k$  average precision of Google Image Search vs. Peculiar Image Retrievals (method: X\*q3) for Japanese object-names.

Next, Table 2 shows each precision for the eight Japanese target object-names and the average precision of the top 20 and top 100 peculiar images retrieved by my refined cross-language Peculiar Image Retrieval (method: JE\*q1-3 and JEJ\*q1-3), my basic single-language Peculiar Image Retrieval (method: J\*q1-3), and Google Image Search (method: J\*q0) as a conventional keyword-based Web image search engine. The values listed in boldface are the best in each Japanese target object-name or the average. It shows that my basic single-language J\*q2 method based on the 2nd type of expanded query ( $q_2 = \text{text: ["cn}_p \text{色の on"}] \text{ AND content: null}$ ) to make a domestic trip in only Japanese as shown in Figure 2 gives the best performance, and that my refined cross-language JEJ\*q2 method based on the 2nd type of expanded query to make a round trip in Japanese  $\rightarrow$  English  $\rightarrow$  Japanese as shown in Figure 6 and my cross-language JEJ\*q3 method based on the 3rd type of expanded query ( $q_3 = \text{text: ["cn}_p \text{色の on"}] \text{ AND content: } cf_p$ ) to make a round trip struggle for the second-best, i.e., cross-language functions seem to be not always effective for Japanese target object-names unlike English target object-names.

Figures 9 and 10 show the top  $k$  average precision of my refined cross-language methods, my basic single-language methods, and Google Image Search for the eight Japanese target object-names. They show that my basic single-language J\*q2 method to make a domestic trip in only Japanese is almost superior to the others, but that my refined cross-language JEJ\*q2 or JEJ\*q3 method to make a round trip from Japanese to English is superior when  $k$  is very small. And they also show that my cross-language JEJ\*qX methods to make a round trip from Japanese to English and my single-language J\*qX methods make a little difference, and my cross-language JE\*qX methods to go from Japanese to English (and not to come back) are worse.

Last, Figures 11 to 19 show the top 20 retrieval results for some English target object-names to compare between Google Image Search, my basic Single-Language Peculiar Image Retrieval, and one of my refined Cross-Language Peculiar Image Retrievals. These figures also show that my refined cross-language methods are superior to my basic single-language method as well as Google Image Search for English target object-names, i.e., cross-language (automatic translation between English and Japanese) functions are very effective for English target object-names. And they show that my refined cross-language methods can retrieve “brown sunflower”; “purple cauliflower”, “orange one”, and “pink one”; “purple tokyo tower”, “green one”, “pink one”, and “blue one” as peculiar images, while my basic single-language method can retrieve “multi-colored sunflower”, “brown one”, and “white one”; “orange cauliflower” and “purple one”; none for “tokyo tower”.

In some cases that no peculiar color-name can be extracted, especially for names of landmarks (in Japan) such as shown in Figure 18, both my basic single-language method and my refined cross-language methods cannot retrieve any image as well as their peculiar images in the top 20 and/or 100 results, while Google Image Search can retrieve some images. I will have to deal with this problem. One approach might be to switch multiple methods, e.g, EJE\*q2 and EJ\*q2 methods for English and J\*q2 and JEJ\*q3 methods for Japanese.

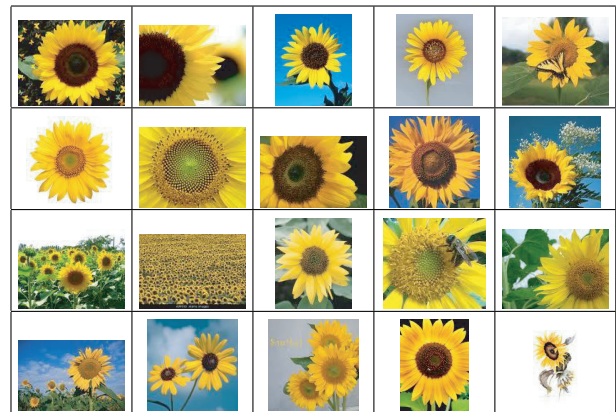


Figure 11: Top 20 results of Google Image Search (method: E\*q0) for English object-name  $on =$  “sunflower”.



Figure 12: Top 20 results of Single-Language Peculiar Image Retrieval (method: E\*q2) for English object-name  $on =$  “sunflower”.

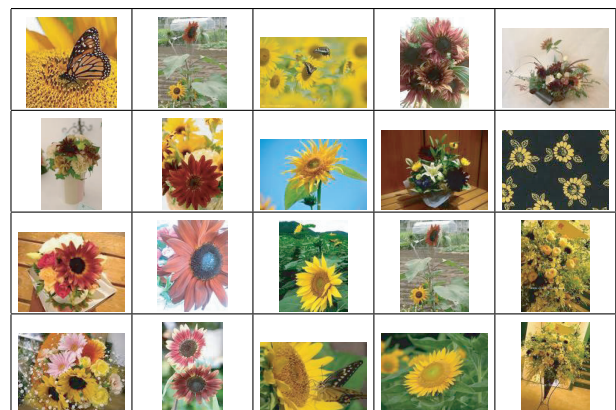
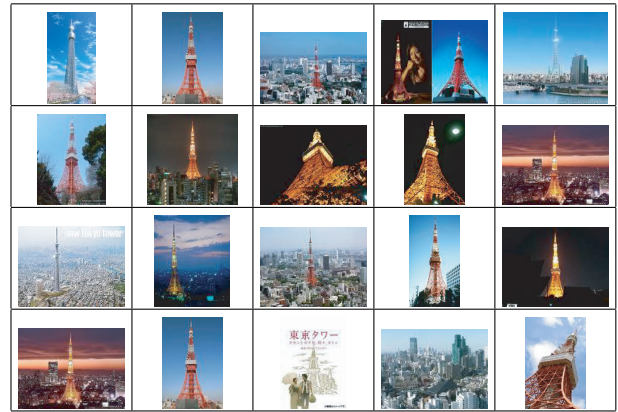


Figure 13: Top 20 results of Cross-Language Peculiar Image Retrieval (method: EJ\*q3) for English object-name  $on =$  “sunflower”.

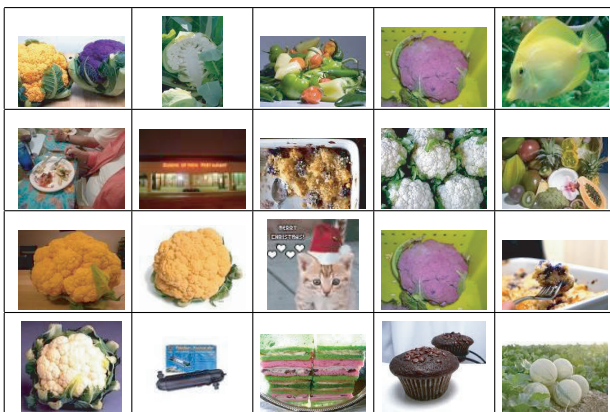




**Figure. 14:** Top 20 results of Google Image Search (method: E\*q0) for English object-name *on* = “cauliflower”.



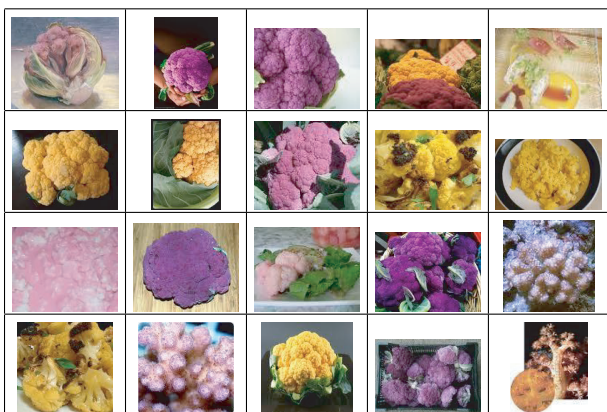
**Figure. 17:** Top 20 results of Google Image Search (method: E\*q0) for English object-name *on* = “tokyo tower”.



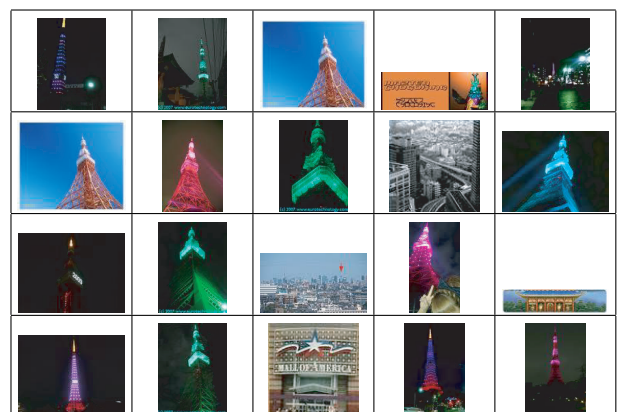
**Figure. 15:** Top 20 results of Single-Language Peculiar Image Retrieval (method: E\*q2) for English object-name *on* = “cauliflower”.

No Image	No Image	No Image	No Image	No Image
No Image	No Image	No Image	No Image	No Image
No Image	No Image	No Image	No Image	No Image
No Image	No Image	No Image	No Image	No Image

**Figure. 18:** Top 20 results of Single-Language Peculiar Image Retrieval (method: E\*q2) for English object-name *on* = “tokyo tower”.



**Figure. 16:** Top20 results of Cross-Language Peculiar Image Retrieval (method: EJE\*q3) for English object-name *on* = “cauliflower”.



**Figure. 19:** Top 20 results of Cross-Language Peculiar Image Retrieval (method: EJE\*q2) for English object-name *on* = “tokyo tower”.

## V. Conclusion

As next steps of Image Retrieval (IR), it is very important to discriminate between “Typical Images” and “Peculiar Images” in the acceptable images for a target object, and moreover, to collect many different kinds of peculiar images as exhaustively as possible. In other words, “Exhaustiveness” is one of the most important requirements in the next IR. As a solution to the 1st next step, this paper has proposed a basic method [5, 6] to precisely retrieve peculiar images of a target object from the Web by its peculiar appearance descriptions (e.g., color-names) extracted from the Web and/or its peculiar image features (e.g., color-features) converted from its peculiar appearance descriptions.

To make the basic method more robust, this paper has also proposed a refined method [10] equipped with cross-language (e.g., translation between Japanese and English) functions. And several experimental results have validated the retrieval precision (robustness) of my cross-language methods for English object-names by comparing with such a conventional keyword-based Web image search engine as Google Image Search and my basic single-language method. My refined cross-language Peculiar Image Retrieval for English target object-names has been about twice as precise as my basic Peculiar Image Retrieval, and about quadrice as precise as Google Image Search.

In the future, I try to utilize the other appearance descriptions (e.g., shape and texture) than color-names and the other image features than color-features in my basic single-language and my refined cross-language Peculiar Image Retrievals, and also plan to evaluate my refined cross-language Peculiar Image Retrievals with translation between the other pairs of languages.

## Acknowledgments

This work was supported in part by JSPS (Japan Society for the Promotion of Science) Grant-in-Aid for Young Scientists (B) “A research on Web Sensors to extract spatio-temporal data from the Web” (#23700129, Project Leader: Shun Hattori, 2011–2012).

## References

- [1] Inder, R., Bianchi-Berthouze, N., and Kato, T., 1999, “K-DIME: A Software Framework for Kansei Filtering of Internet Material,” Proceedings of IEEE International Conference on Systems, Man and Cybernetics (SMC’99), Vol.6, pp.241–246.
- [2] Kurita, T., Kato, T., Fukuda, I., and Sakakura, A., 1992, “Sense Retrieval on a Image Database of Full Color Paintings,” Transactions of Information Processing Society of Japan (IPSJ), Vol.33, No.11, pp.1373–1383.
- [3] Kimoto, H., 1999, “An Image Retrieval System Using Impressional Words and the Evaluation of the System,” Transactions of Information Processing Society of Japan (IPSJ), Vol.40, No.3, pp.886–898.
- [4] Hattori, S. and Tanaka, K., 2008, “Search the Web for Typical Images based on Extracting Color-names from the Web and Converting them to Color-Features,” Letters of Database Society of Japan (DBSJ), Vol.6, No.4, pp.9–12.
- [5] Hattori, S. and Tanaka, K., 2010, “Search the Web for Peculiar Images by Converting Web-extracted Peculiar Color-Names into Color-Features,” IPSJ Transactions on Databases, Vol.3, No.1 (TOD45), pp.49–63.
- [6] Hattori, S., 2010, “Peculiar Image Search by Web-extracted Appearance Descriptions,” Proceedings of the 2nd International Conference on Soft Computing and Pattern Recognition (SoCPaR’10), pp.127–132.
- [7] Yamamoto, T., Nakamura, S., and Tanaka, K., 2007, “Rerank-By-Example: Browsing Web Search Results Exhaustively Based on Edit Operations,” Letters of DBSJ, Vol.6, No.2, pp.57–60.
- [8] Hattori, S., Tezuka, T., and Tanaka, K., 2007, “Extracting Visual Descriptions of Geographic Features from the Web as the Linguistic Alternatives to Their Images in Digital Documents,” IPSJ Transactions on Databases, Vol.48, No.SIG11 (TOD34), pp.69–82.
- [9] Hattori, S., Tezuka, T., and Tanaka, K., 2007, “Mining the Web for Appearance Description,” Proceedings of the 18th International Conference on Database and Expert Systems Applications (DEXA’07), LNCS Vol.4653, pp.790–800.
- [10] Hattori, S., 2011, “Cross-Language Peculiar Image Search Using Translation between Japanese and English,” Proceedings of the 2011 First IRAST International Conference on Data Engineering and Internet Technology (DEIT’11), pp.418–424.
- [11] Japanese Industrial Standards Committee, “Names of Non-Luminous Object Colours,” JIS Z 8102:2001.
- [12] Wikipedia – List of colors, 2011, [http://en.wikipedia.org/wiki/List\\_of\\_colors](http://en.wikipedia.org/wiki/List_of_colors).
- [13] Smith, J. R. and Chang, S.-F., 1996, VisualSEEK: A Fully Automated Content-Based Image Query System, Proceedings of the 4th ACM International Conference on Multimedia (ACM Multimedia’96), pp.87–98.

## Author Biographies

**Shun Hattori** was born in Amagasaki, Japan on September 1st, 1981. He received his B.E., M.I., and Ph.D. degrees in Informatics from Kyoto University, Japan, in 2004, 2006, and 2009, respectively. From April to September of 2009, he was a Researcher at Geosphere Research Institute of Saitama University (GRIS), Japan, where he was involved in development of an earthquake report system “ZiSyn”. In October of 2009, he joined the School of Computer Science, Tokyo University of Technology, Japan, where he is an Assistant Professor currently. His research interests include Web search, Web intelligence, and access control, especially in mobile/ubiquitous computing environments. He is a member of the IPSJ, IEICE, DBSJ, and IEEE.