International Journal of Computer Information Systems and Industrial Management Applications.
ISSN 2150-7988 Volume 5 (2013) pp. 079–088

Hyponymy-Based Peculiar Image Retrieval

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Abstract: **Most researches on Image Retrieval (IR) have aimed at clearing away noisy images and enabling 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 to a conventional keyword-based Web image search engine. However, because the search results rarely include its uncommon images, we can often get only its common (maybe similar) images and cannot easily get exhaustive knowledge about its appearance (look and feel). As next steps of IR, 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 exhaustively. This paper proposes novel methods to retrieve peculiar images from the Web by expanding or modifying a target object-name (as an original query) with its hyponyms, which are based on hand-made concept hierarchies such as WordNet and Wikipedia, or which are extracted from the Web by text mining techniques, and validates their precision by comparing with Google Image Search.**
Keywords: Image Search, Web Search, Web Mining, Hyponymy, Concept Hierarchy, Peculiar Image, Typical Image.

I. Introduction

In recent years, various demands have arisen in searching the Web for images as well as documents (text) to utilize them 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 enable 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. One example of more niche image retrievals enables the user to get special images of the target object with the impression [1, 2, 3, 4, 5].

Another example of more niche demands, when only a name of a target object is given, is to search the Web for its "Typical Images" [6, 7] which enable us to adequately figure out its typical appearance features and easily associate themselves with the correct object-name, and its "Peculiar Images" [8, 9, 10, 11] 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 "sapphire" with "blue one", while there also exists "red sunflower" or "black one" etc., "purple cauliflower" or "orange one" etc., and "yellow sapphire" or "pink 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 typical ones.

Conventional Web image search engines are mostly Text-Based Image Retrievals by using the filename, alternative text, and surrounding text of each Web image. When such a text-based condition as a name of a target object is given by a user, they give the user the searched 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 search results, while peculiar images rarely appear in the top tens of the search results. 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.

My early work [8, 9] has proposed a method to search the Web for peculiar images of a target object whose 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 [12, 13, 14] 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, my previous work [10, 11] has proposed a refined method equipped with cross-language (translation between Japanese and English) functions like [15, 16]. As another solution, this paper proposes novel methods to retrieve peculiar images from the Web by expanding or modifying a target object-name (as an original query) with its hyponyms, which are based on hand-made concept hierarchies such as WordNet and Wikipedia [17], or which are extracted mechanically from enormous Web documents by text mining techniques [18]. And this paper shows several experimental results to validate their precision by comparing with Google Image Search.

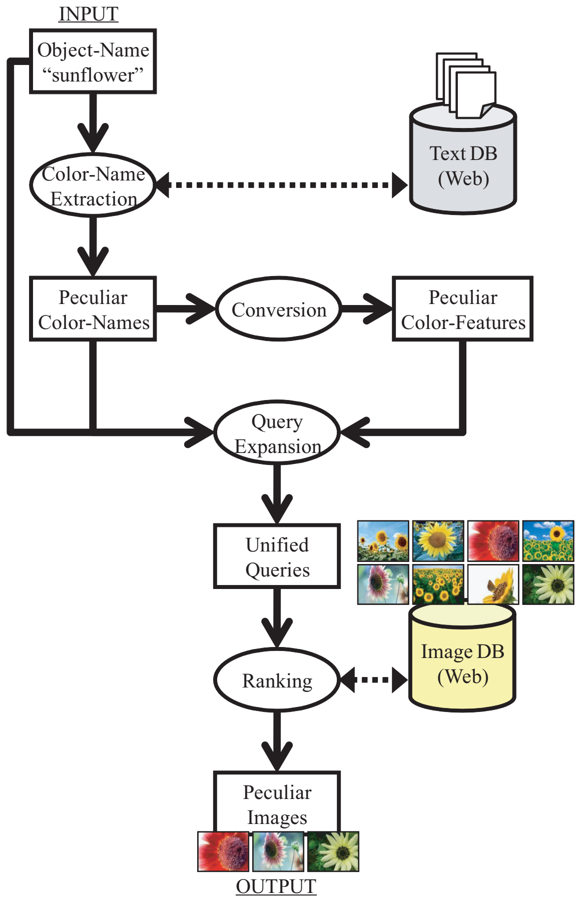


Figure. 1: Peculiar Image Retrieval based on peculiar color-names extracted from the Web.

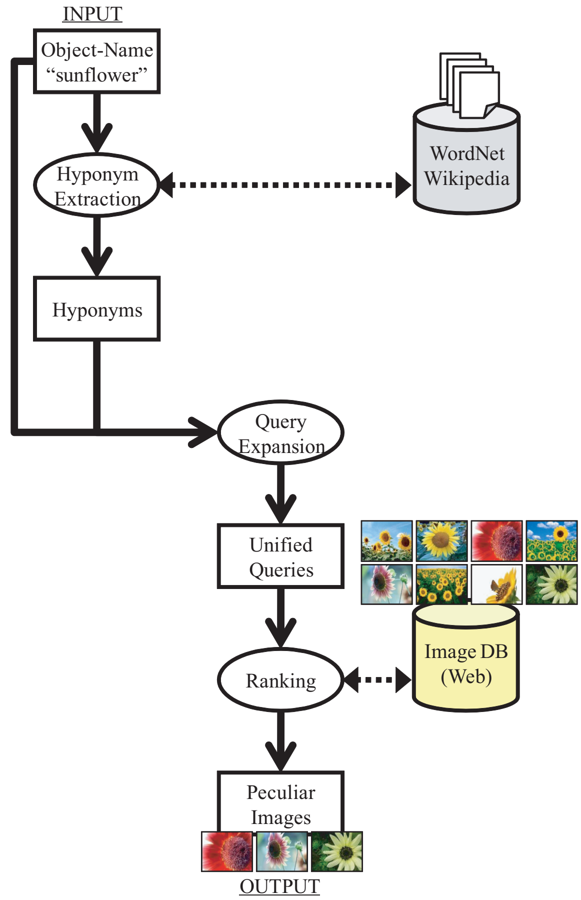


Figure. 2: Peculiar Image Retrieval based on peculiar hyponyms extracted from hand-made WordNet and Wikipedia.

II. Method: Peculiar Image Retrieval based on Hand-made Hyponyms

This section proposes a novel method [17] to precisely search the Web for "Peculiar Images" of a target object whose name is given as a user's original query, by expanding the original query with its hyponyms based on hand-made concept hierarchies such as WordNet and Wikipedia.
While Figure 1 gives an overview of my previous Peculiar Image Retrieval [9] based on Web-extracted color-names as appearance descriptions, Figure 2 gives an overview of my proposed Peculiar Image Retrieval (PIR) based on hand-made hyponym relations.

Step 1. Hyponym Extraction

When a name of a target object as an original query is given by a user, its hyponyms are extracted from hand-made concept hierarchies such as WordNet and Wikipedia. Of course, they could be mechanically extracted from exploding Web documents about the target object by text mining techniques [14, 19, 20, 21]. The former is precision-oriented, while the latter is rather recall-oriented. Therefore, this section adopts the former as a solution of the 1st next step of Image Retrieval to precisely discriminate between "Typical Images" and "Peculiar Images" in the acceptable images.

Step 2. Query Expansion by Hyponyms

Here, we have two kinds of clues to retrieve peculiar images from the Web: not only a target object-name o (text-based condition) as an original query given by a user, but also its hyponyms h (text-based condition) extracted from WordNet and/or Wikipedia in the Step 1. There is no content-based condition for CBIR [22].
The original query (q0 = text: ["o"] & content: null) can be modified or expanded by its hyponym h as follows:

q1 = text: ["h"] & content: null,

q2 = text: ["o" AND "h"] & content: null.

More conditioned latter is adopted to precisely retrieve its acceptable images and "Peculiar Images" from the Web.

Step 3. Image Ranking by Expanded Queries

This section defines two kinds of weights $\mathrm{pir}_{1/2}(i,o)$ of Peculiar Image Retrieval based on the expanded query (q2 = text: ["o" AND "h"] & content: null) in the Step 2.
The first (simpler) weight $\mathrm{pir}_1(i,o)$ is assigned to a Web image i for a target object-name o and is defined as

$$\mathrm{pir}_1(i,o) := \max_{\forall h \in H(o)} \left\{ \frac{\mathrm{hyponym}(h,o)}{\mathrm{rank}(i,o,h)^2} \right\},$$

where $H(o)$ stands for a set of hyponyms of a target object-name o from the WordNet and/or Wikipedia in the Step 1, a Web image i is searched by submitting the text-based query ["o" AND "h"] (e.g., ["sunflower" AND "evening sun"]) to Google Image Search, and $\mathrm{rank}(i,o,h)$

stands for the rank of a Web image i in the search results. And hyponym(h, o) stands for the suitability of a candidate h for hyponyms of a target object-name o. In this section, hyponym(h, o) is always set to 1 for any hyponym candidate h of a target object-name o because they are extracted from hand-made (so certainly precise) concept hierarchies such as WordNet and Wikipedia. So, the first weight can be re-defined as

$$\text{pir}_1(i, o) := \max_{\forall h \in H(o)} \left\{ \frac{1}{\text{rank}(i, o, h)^2} \right\}.$$

The second (more sophisticated) weight $\text{pir}_2(i, o)$ using the suitability $\text{ph}(h, o)$ is assigned to a Web image i for a target object-name o and is defined as

$$\text{pir}_2(i, o) := \max_{\forall h \in H(o)} \left\{ \frac{\text{ph}(h, o)}{\text{rank}(i, o, h)} \right\},$$

where $\text{ph}(h, o)$ stands for the suitability of a candidate h for Peculiar(-colored) Hyponyms of a target object-name o,

$$\begin{aligned} \text{ph}(h, o) \quad &:= \frac{|I_k(o)| \cdot |I_k(o, h)| \cdot \text{hyponym}(h, o)}{\displaystyle\sum_{i \in I_k(o)} \sum_{j \in I_k(o,h)} \text{sim}(i, j)} \\ &= \frac{|I_k(o)| \cdot |I_k(o, h)|}{\displaystyle\sum_{i \in I_k(o)} \sum_{j \in I_k(o,h)} \text{sim}(i, j)}, \end{aligned}$$

where $I_k(o)$ and $I_k(o, h)$ stand for a set of the top (at most) k Web images searched by submitting the text-based query `["o"]` (e.g., `["sunflower"]`) and `["o" AND "h"]` (e.g., `["sunflower" AND "evening sun"]`) to Google Image Search, respectively. In this section, k is set to 100. And $\text{sim}(i, j)$ stands for the similarity between Web images i and j in the HSV color space [23] as a cosine similarity,

$$\text{sim}(i, j) := \frac{\displaystyle\sum_{\forall c} \text{prop}(c, i) \cdot \text{prop}(c, j)}{\sqrt{\displaystyle\sum_{\forall c} \text{prop}(c, i)^2} \sqrt{\displaystyle\sum_{\forall c} \text{prop}(c, j)^2}},$$

where $\forall c$ stands for any color-feature in the HSV color space with 12 divides for Hue, 5 divides for Saturation, and 1 divide for Value (Brightness), and $\text{prop}(c, i)$ stands for the proportion of a color-feature c in a Web image i.

III. Method: Peculiar Image Retrieval based on Web-extracted Hyponyms

This section proposes another novel method [18] to precisely search the Web for "Peculiar Images" of a target object whose name is given as a user's original query, by expanding the original query with its hyponyms extracted mechanically from the whole Web by text mining techniques.

While Figure 1 gives an overview of my previous Peculiar Image Retrieval [9] based on Web-extracted color-names as appearance descriptions, Figure 3 gives an overview of my proposed Peculiar Image Retrieval (PIR) based on Web-extracted hyponym relations.

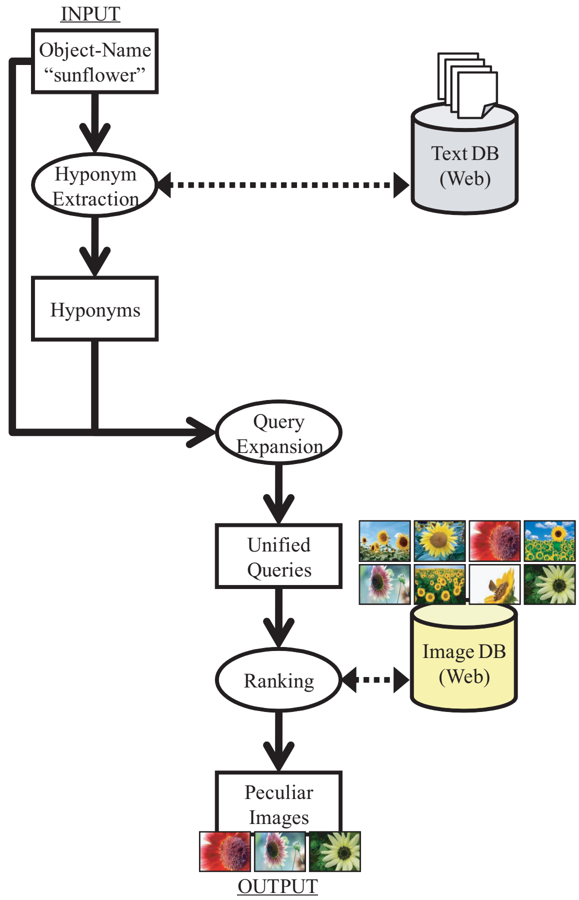


Figure. 3: Peculiar Image Retrieval based on peculiar hyponyms extracted from the miscellaneous Web.

Step 1. Hyponym Extraction

When a name of a target object as an original query is given by a user, its hyponyms are mechanically extracted from exploding Web documents about the target object by text mining techniques [14, 19, 20, 21]. Of course, they could be extracted from hand-made concept hierarchies such as WordNet and Wikipedia. The latter is precision-oriented, while the former is rather recall-oriented. Therefore, this section adopts the former as a solution of the 2nd next step of Image Retrieval to collect many different kinds of peculiar images as exhaustively as possible.

The PIR system collects candidates for hyponyms of a target object-name o (e.g., "sunflower") by using two kinds of lexico-syntactic patterns "a * o" (e.g., "a pink sunflower") and "the * o" (e.g., "the maximillian sunflower") where "*" is wild-card. Next, the system filters out "* o" (e.g., "14-headed sunflower") whose frequency of Web documents searched by submitting `["* o"]` as a query to Google Web Search is less than 10, and uses only the top (at most) 100 candidates ordered by their document frequency.

Step 2. Query Expansion by Hyponyms

Here, we have two kinds of clues to retrieve peculiar images from the Web: not only a target object-name o (text-based condition) as an original query given by a user, but also its hyponyms h (text-based condition) extracted mechanically from not hand-made concept hierarchies such as WordNet but the miscellaneous Web in the Step 1.

The original query (q0 = text: ["o"] & content: null) can be modified or expanded by its hyponym h as follows:

q1 = text: ["h"] & content: null,

q2 = text: ["o" AND "h"] & content: null.

More conditioned latter is adopted to precisely retrieve its acceptable images and "Peculiar Images" from the Web.

Step 3. Image Ranking by Expanded Queries

This section defines two kinds of weights $\mathrm{pir}_{1/2}(i,o)$ of Peculiar Image Retrieval based on the expanded query (q2 = text: ["o" AND "h"] & content: null) in the Step 2.
The first (simpler) weight $\mathrm{pir}_1(i,o)$ is assigned to a Web image i for a target object-name o and is defined as

$$\mathrm{pir}_1(i,o) := \max_{\forall h \in H(o)} \left\{ \frac{\mathrm{hyponym}(h,o)}{\mathrm{rank}(i,o,h)^2} \right\},$$

where $H(o)$ stands for a set of hyponyms of a target object-name o extracted from the whole Web or the hand-made WordNet in the Step 1, a Web image i is searched by submitting the text-based query ["o" AND "h"] (e.g., ["sunflower" AND "pink sunflower"]) to Google Image Search, and $\mathrm{rank}(i,o,h)$ stands for the rank (positive integer) of a Web image i in the search results from the Google's image database. And $\mathrm{hyponym}(h,o) \in [0,1]$ stands for the weight of a candidate h for hyponyms of a target object-name o. In this section, for any hyponym candidate h of a target object-name o extracted from the hand-made (so certainly precise) WordNet, $\mathrm{hyponym}(h,o)$ is set to 1 (the most precise). Meanwhile, for any Web-extracted hyponym candidate h of a target object-name o, $\mathrm{hyponym}(h,o)$ is calculated as,

$$\mathrm{hyponym}(h,o) := \frac{\mathrm{df}(\texttt{["}h\texttt{"]})}{\max\limits_{\forall h \in H(o)} \{\mathrm{df}(\texttt{["}h\texttt{"]})\}},$$

where $\mathrm{df}([q])$ stands for the frequency of Web documents searched by submitting a query q to Google Web Search.
The second (more sophisticated) weight $\mathrm{pir}_2(i,o)$ is assigned to a Web image i for a target object-name o and is defined as

$$\mathrm{pir}_2(i,o) := \max_{\forall h \in H(o)} \left\{ \frac{\mathrm{ph}(h,o)}{\mathrm{rank}(i,o,h)} \right\},$$

where $\mathrm{ph}(h,o) \in [0,1]$ stands for the weight of a candidate h for Peculiar(-colored) Hyponyms of an object-name o,

$$\mathrm{ph}(h,o) := \frac{(\mathrm{ph}^*(h,o) - \min(o))^2}{(\max(o) - \min(o))^2},$$

$$\mathrm{ph}^*(h,o) := \frac{|I_k(o)| \cdot |I_k(o,h)| \cdot \sqrt{\mathrm{hyponym}(h,o)}}{\sum\limits_{i \in I_k(o)} \sum\limits_{j \in I_k(o,h)} \mathrm{sim}(i,j)},$$

$$\max(o) := \max_{\forall h}\{\mathrm{ph}^*(h,o)\}, \quad \min(o) := \min_{\forall h}\{\mathrm{ph}^*(h,o)\},$$

where $I_k(o)$ and $I_k(o,h)$ stand for a set of the top (at most) k Web images searched by submitting the text-based query ["o"] (e.g., ["sunflower"]) and ["o" AND "h"] (e.g., ["sunflower" AND "pink sunflower"]) to Google Image Search, respectively. In this section, k is set to 100. And $\mathrm{sim}(i,j)$ stands for the similarity between Web images i and j in the HSV color space [23] as a cosine similarity,

$$\mathrm{sim}(i,j) := \frac{\sum\limits_{\forall c} \mathrm{prop}(c,i) \cdot \mathrm{prop}(c,j)}{\sqrt{\sum\limits_{\forall c} \mathrm{prop}(c,i)^2} \sqrt{\sum\limits_{\forall c} \mathrm{prop}(c,j)^2}},$$

where $\forall c$ stands for any color-feature in the HSV color space with 12 divides for Hue, 5 divides for Saturation, and 1 divide for Value (Brightness), and $\mathrm{prop}(c,i)$ stands for the proportion of a color-feature c in a Web image i.

IV. Experiments

A. Peculiar Image Retrieval by Hand-made Hyponyms

Several experimental results for the following four kinds of target object-names for Peculiar Image Retrieval are shown to validate my proposed method to precisely retrieve their peculiar images from the Web based on hand-made concept hierarchies such as WordNet and Wikipedia, by comparing with Google Image Search as a conventional keyword-based Web image search engine.

Table 1: Number of hyponyms in WordNet and/or Wikipedia.

Object-Name	WordNet	Wikipedia	both
sunflower	19	45	60
cauliflower	0	36	36
praying mantis	0	800	800
sapphire	1	15	15

Figure 4 shows the top k average precision of my proposed Peculiar Image Retrieval (PIR) based on hand-made concept hierarchies such as WordNet and Wikipedia, and Google Image Search. It shows that my PIR method by using the second (more sophisticated) ranking function $\mathrm{pir}_2(i,o)$ with the suitability $\mathrm{ph}(h,o)$ of a candidate h extracted from (hand-made) concept hierarchies for peculiar(-colored) hyponyms of a target object-name o is superior to my PIR method by using the first (simpler) ranking function $\mathrm{pir}_1(i,o)$ without the suitability $\mathrm{ph}(h,o)$ as well as Google Image Search, and that my PIR method by using Wikipedia's hyponym relations is superior to my PIR method by using WordNet's hyponym relations.

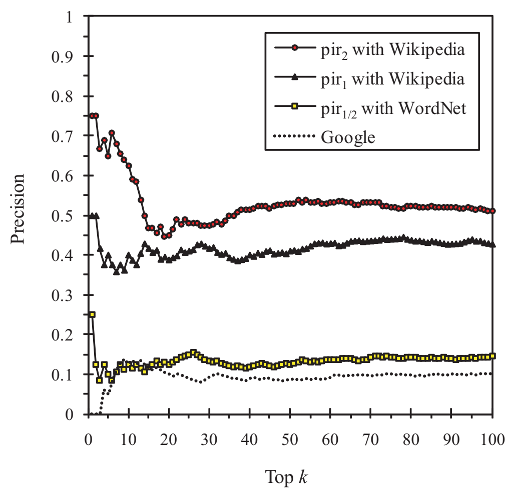
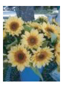


Figure. 4: Top k average precision of Google Image Search vs. Peculiar Image Retrieval by hand-made hyponyms.

Table 2 includes the top 10 peculiar(-colored) hyponyms h of a target object-name o = “sunflower” ranked by using their suitability $\mathrm{ph}(h, o)$ for the second (more sophisticated) ranking function $\mathrm{pir}_2(i, o)$ with Wikipedia’s hyponym relations. The hyponyms indicated by boldface are acceptable for its peculiar hyponyms. Many acceptable peculiar hyponyms can be ranked high, but several noisy words (e.g., “black oil” at 3rd) are ranked higher than the other peculiar hyponyms (e.g., “evening sun” at 18th).
Figures 5 to 7 show the top 20 retrieval results for a target object-name o = “sunflower” to compare between Google Image Search, and my proposed Peculiar Image Retrieval by using the first (simpler) ranking function $\mathrm{pir}_1(i, o)$ or the second (more sophisticated) ranking function $\mathrm{pir}_2(i, o)$ based on Wikipedia’s hyponym relations.

Table 2: Peculiar hyponyms of object-name o = “sunflower” extracted from Wikipedia with typical images.

Rank	Peculiar Hyponym h	$\mathrm{ph}(h, o)$	Typical Image
1	**velvet queen**	5.37327	
2	**italian white**	5.11842	
3	black oil	5.07947	
4	**red sun**	4.46867	
5	sunchoke	4.24779	
6	**aztec sun**	4.23808	
7	**strawberry blonde**	4.16153	
8	peredovik	3.83770	
9	**tithonia rotundifolia**	3.81871	
10	north american sunflower	3.78737	
12	**peach passion**	3.76906	
13	**indian blanket hybrid**	3.58879	
14	**evening sun**	3.43408	

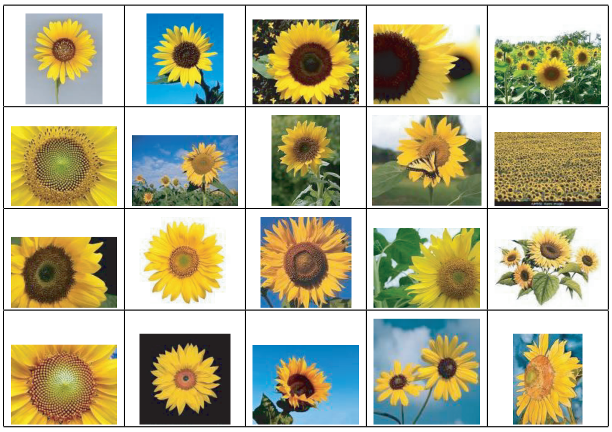


Figure. 5: Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: “sunflower”).

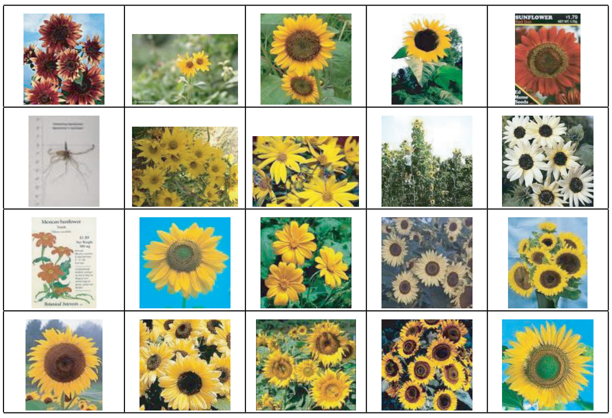


Figure. 6: Top 20 results of Peculiar Image Retrieval with Wikipedia-extracted hand-made hyponyms (query: q2, ranking: $\mathrm{pir}_1(i, o)$, object-name: “sunflower”).

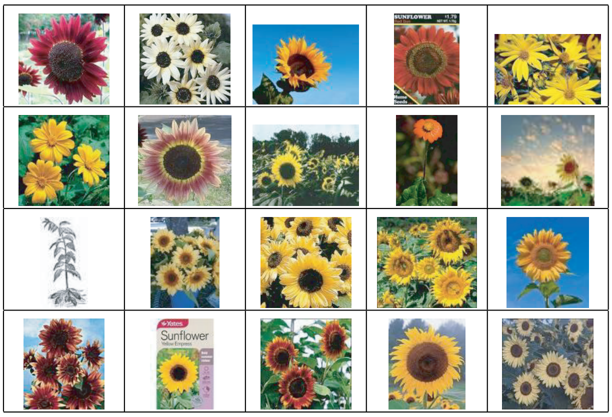


Figure. 7: Top 20 results of Peculiar Image Retrieval with Wikipedia-extracted hand-made hyponyms (query: q2, ranking: $\mathrm{pir}_2(i, o)$, object-name: “sunflower”).

Table 3 includes the top 10 peculiar(-colored) hyponyms h of a target object-name $o =$ “cauliflower” ranked by using their suitability $\mathrm{ph}(h, o)$ for the second (more sophisticated) ranking function $\mathrm{pir}_2(i, o)$ with Wikipedia’s hyponym relations. The hyponyms indicated by boldface are acceptable for its peculiar hyponyms. Many acceptable peculiar hyponyms can be ranked high, but some noisy words (e.g., “igloo” at 7th) are ranked higher than the other peculiar hyponyms (e.g., “romanesco broccoli” at 19th).
Figures 8 to 10 show the top 20 search results for a target object-name $o =$ “cauliflower” to compare between Google Image Search, and my proposed Peculiar Image Retrieval by using the first (simpler) ranking function $\mathrm{pir}_1(i, o)$ or the second (more sophisticated) ranking function $\mathrm{pir}_2(i, o)$ based on Wikipedia’s hyponym relations.

Table 3: Peculiar hyponyms of object-name $o =$ “cauliflower” extracted from Wikipedia with typical images.

Rank	Peculiar Hyponym h	$\mathrm{ph}(h, o)$	Typical Image
1	**purple cape**	4.64476	
2	**graffiti**	4.59797	
3	**purple cauliflower**	4.42077	
4	**violetta italia**	3.43158	
5	**minaret**	3.42849	
6	**veronica**	3.34011	
7	igloo	3.31682	
8	candid charm	3.27989	
9	mayflower	3.26645	
10	**cheddar**	3.16336	
11	**green cauliflower**	3.15210	
12	**orange cauliflower**	3.13397	
13	**romanesco broccoli**	3.03155	

Figure. 8: Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: “cauliflower”).

Figure. 9: Top 20 results of Peculiar Image Retrieval with Wikipedia-extracted hand-made hyponyms (query: q2, ranking: $\mathrm{pir}_1(i, o)$, object-name: “cauliflower”).

Figure. 10: Top 20 results of Peculiar Image Retrieval with Wikipedia-extracted hand-made hyponyms (query: q2, ranking: $\mathrm{pir}_2(i, o)$, object-name: “cauliflower”).

B. Peculiar Image Retrieval by Web-extracted Hyponyms

Several experimental results for the following six kinds of target object-names for Peculiar Image Retrieval are shown to validate my proposed method to retrieve their peculiar images from the Web more precisely than conventional Web image search engines such as Google Image Search. Table 4 shows the number of WordNet's and Web-extracted hyponyms for each object.

Table 4: Number of hyponyms from WordNet and the Web.

Object-Name	**WordNet**	**Web-extracted**	
sunflower	19	100	(of 531)
cauliflower	0	100	(of 368)
praying mantis	0	100	(of 253)
tokyo tower	0	92	(of 157)
nagoya castle	0	23	(of 57)
wii	0	100	(of 297)

Figure 11 shows the top k average precision of my proposed Peculiar Image Retrieval (PIR) based on Web-extracted hyponyms or hand-made concept hierarchies such as WordNet, and Google Image Search for the above-mentioned six target object-names. It shows that my PIR methods by using Web-extracted hyponym relations are superior to my PIR method by using WordNet's hand-made hyponym relations as well as Google Image Search, and that my PIR method by using the second (more sophisticated) ranking $\text{pir}_2(i, o)$ with the suitability $\text{ph}(h, o)$ of a candidate h extracted from the Web for peculiar(-colored) hyponyms of a target object-name o is marginally superior to my PIR method by using the first (simpler) ranking $\text{pir}_1(i, o)$ without the suitability $\text{ph}(h, o)$.
Figures 12 to 14 and Figures 15 to 17 show the top 20 search results for a target object-name o = "tokyo tower" and "nagoya castle" respectively to compare between Google Image Search, and my proposed Peculiar Image Retrieval by using the first (simpler) ranking function $\text{pir}_1(i, o)$ or the second (more sophisticated) ranking function $\text{pir}_2(i, o)$ based on Web-extracted hyponym relations.

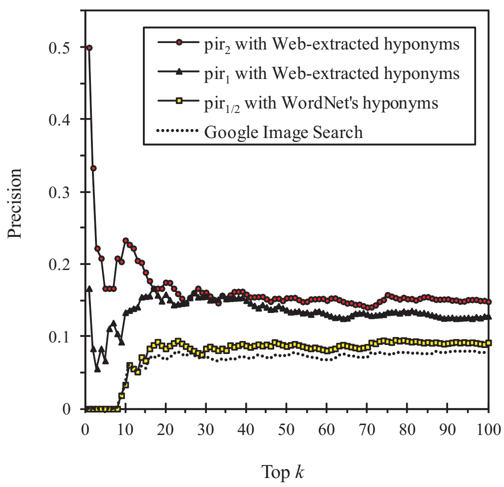


Figure. 11: Top k average precision of Google Image Search vs. Peculiar Image Retrieval by Web-extracted hyponyms.

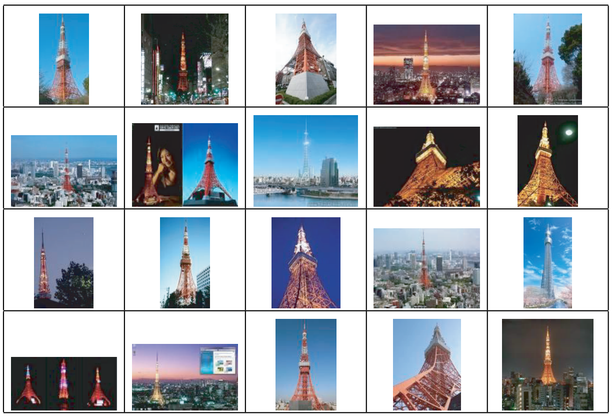


Figure. 12: Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: "tokyo tower").

Figure. 13: Top 20 results of Peculiar Image Retrieval with Web-extracted peculiar(-colored) hyponyms (query: q2, ranking: $\text{pir}_1(i, o)$, object-name: "tokyo tower").

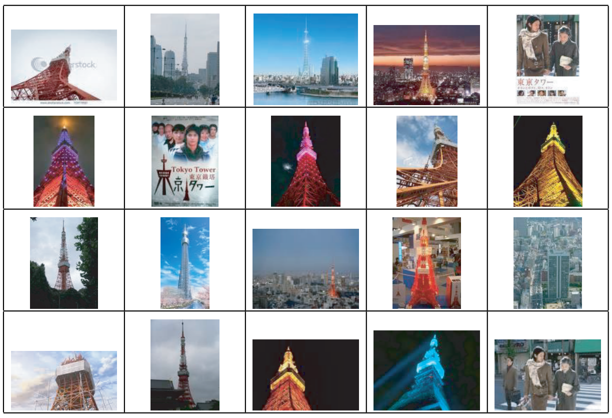


Figure. 14: Top 20 results of Peculiar Image Retrieval with Web-extracted peculiar(-colored) hyponyms (query: q2, ranking: $\text{pir}_2(i, o)$, object-name: "tokyo tower").

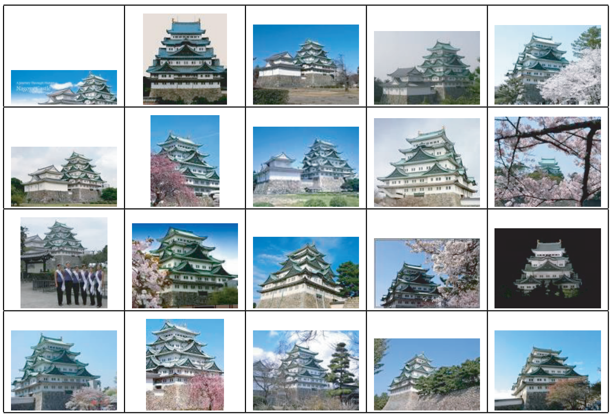


Figure. 15: Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: "nagoya castle").

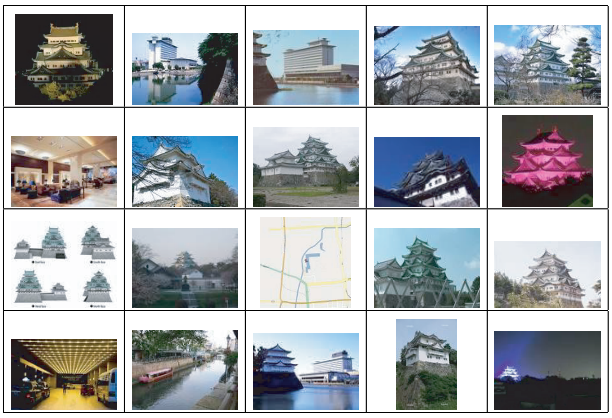


Figure. 16: Top 20 results of Peculiar Image Retrieval with Web-extracted peculiar(-colored) hyponyms (query: q2, ranking: $\mathrm{pir}_1(i, o)$, object-name: "nagoya castle").

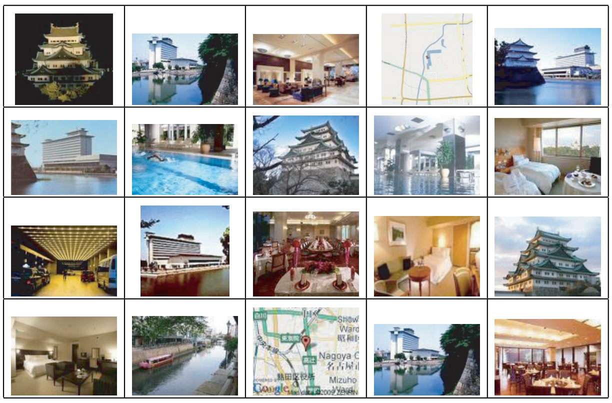


Figure. 17: Top 20 results of Peculiar Image Retrieval with Web-extracted peculiar(-colored) hyponyms (query: q2, ranking: $\mathrm{pir}_2(i, o)$, object-name: "nagoya castle").

Tables 5 and 6 show the top 20 peculiar hyponyms with peculiar color-features of a target object-name, "sunflower" and "cauliflower", respectively. They show that $\mathrm{ph}(h, o)$ used by the second (more refined) ranking $\mathrm{pir}_2(i, o)$ is superior to $\mathrm{hyponym}(h, o)$ used by the first (simpler) ranking $\mathrm{pir}_2(i, o)$ as a weighting function of peculiar hyponyms h for each target object-name o. Figure 18 shows the top k average precision of hyponym extraction from the Web. $\mathrm{ph}(h, o)$ gives 42.5% (not much different) precision at $k = 20$ for hyponym extraction, while $\mathrm{hyponym}(h, o)$ gives 42.5% precision. And Figure 19 shows the top k average precision of peculiar hyponym extraction from the Web. $\mathrm{ph}(h, o)$ gives 16.7% (superior) precision at $k = 20$ for peculiar hyponym extraction, while $\mathrm{hyponym}(h, o)$ gives 10.0% precision.

Table 5: Top 20 peculiar hyponyms of "sunflower".

	hyponym(h, o)		ph(h, o)	
1	good sunflower	1.000	**pink sunflower**	1.000
2	tall sunflower	1.000	raw sunflower	0.789
3	ground sunflower	0.984	shelled sunflower	0.770
4	same sunflower	0.968	brunning sunflower	0.758
5	few sunflower	0.964	roasted sunflower	0.669
6	small sunflower	0.929	complex sunflower	0.645
7	first sunflower	0.915	hotel sunflower	0.533
8	giant sunflower	0.913	**purple sunflower**	0.511
9	raw sunflower	0.910	**green sunflower**	0.493
10	growing sunflower	0.900	**black sunflower**	0.470
11	new sunflower	0.900	black oil sunflower	0.386
12	huge sunflower	0.898	gray sunflower	0.370
13	black oil sunflower	0.890	modern sunflower	0.357
14	complex sunflower	0.890	**metal sunflower**	0.335
15	brunning sunflower	0.878	emmanuelle sunflower	0.332
16	large sunflower	0.876	dried sunflower	0.331
17	toasted sunflower	0.875	given sunflower	0.289
18	tiny sunflower	0.868	**blue sunflower**	0.282
19	normal sunflower	0.856	**red sunflower**	0.277
20	u.s. sunflower	0.855	kids' sunflower	0.223

Table 6: Top 20 peculiar hyponyms of "cauliflower".

	hyponym(h, o)		ph(h, o)	
1	spicy cauliflower	1.000	**purple cauliflower**	1.000
2	grated cauliflower	1.000	**pink cauliflower**	0.455
3	remaining cauliflower	1.000	fried cauliflower	0.268
4	**purple cauliflower**	0.984	spicy cauliflower	0.255
5	blanched cauliflower	0.975	**yellow cauliflower**	0.234
6	creamy cauliflower	0.975	few cauliflower	0.230
7	leftover cauliflower	0.965	huge cauliflower	0.230
8	fried cauliflower	0.948	grated cauliflower	0.191
9	raw cauliflower	0.948	regular cauliflower	0.186
10	boiled cauliflower	0.944	curried cauliflower	0.179
11	huge cauliflower	0.940	tiny cauliflower	0.168
12	**yellow cauliflower**	0.934	**golden cauliflower**	0.166
13	organic cauliflower	0.932	crispy cauliflower	0.148
14	crunchy cauliflower	0.928	little cauliflower	0.140
15	or cauliflower	0.905	tandoori cauliflower	0.139
16	baby cauliflower	0.904	**cheddar cauliflower**	0.129
17	tiny cauliflower	0.898	leftover cauliflower	0.123
18	**golden cauliflower**	0.884	yummy cauliflower	0.120
19	garlic cauliflower	0.877	larger cauliflower	0.116
20	drained cauliflower	0.874	braised cauliflower	0.115

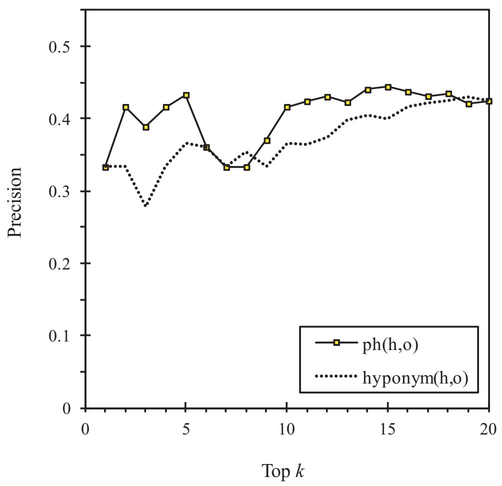


Figure. 18: Top k average precision of Web-extracted hyponyms by two kinds of ranking functions.

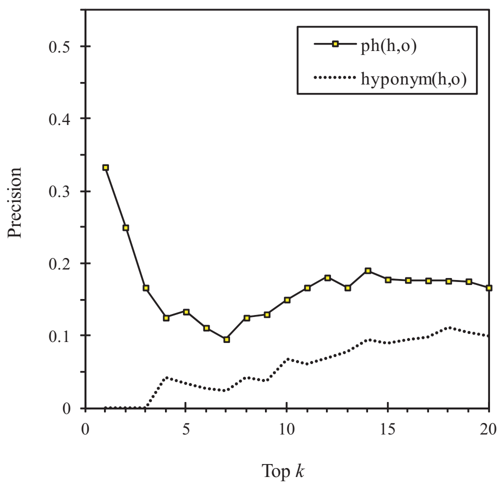


Figure. 19: Top k average precision of Web-extracted peculiar hyponyms by two kinds of ranking functions.

V. Conclusions

As next steps of Image Retrieval (IR), it is very important to discriminate between "Typical Images" [6, 7] and "Peculiar Images" [8, 9, 10, 11] in the acceptable images of a target object specified by its object-name, and moreover, to collect many different kinds of peculiar images exhaustively. In other words, "Exhaustiveness" is one of the most important requirements in the next IR.

My early work [8, 9] proposed a basic method 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 the Web-extracted peculiar appearance descriptions. And to make the basic method more robust, my previous work [10, 11] proposed a refined method equipped with cross-language (mechanical translation between Japanese and English) functions.

As one solution, this paper has proposed a novel method [17] to retrieve peculiar images from the Web by expanding or modifying a target object-name (as a user's original query) with its hyponyms based on hand-made concept hierarchies such as WordNet and Wikipedia. And several experimental results have validated the search precision of my proposed method by comparing with such a conventional keyword-based Web image search engine as Google Image Search. They also have shown that my second (more sophisticated) image-ranking function $\mathrm{pir}_2(i, o)$ with the suitability $\mathrm{ph}(h, o)$ of a candidate h extracted from (hand-made) concept hierarchies for peculiar(-colored) hyponyms of a target object-name o is superior to my first (simpler) image-ranking function $\mathrm{pir}_1(i, o)$ without the suitability $\mathrm{ph}(h, o)$, and that the Wikipedia is superior to the WordNet as a Web source of hand-made hyponym relations for my proposed Peculiar Image Search based on (hand-made) concept hierarchies.

As another solution, this paper has proposed a novel method [18] to retrieve peculiar images from the Web by expanding or modifying a target object-name (as a user's original query) with its hyponyms extracted mechanically from the Web by using not hand-made concept hierarchies such as WordNet but enormous Web documents and text mining techniques. And several experimental results have validated the retrieval precision of my proposed method by comparing with such a conventional keyword-based Web image search engine as Google Image Search. They also have shown that my second (more sophisticated) ranking $\mathrm{pir}_2(i, o)$ is marginally superior to my first (simpler) ranking $\mathrm{pir}_1(i, o)$, and that using Web-extracted hyponym relations is superior to using hand-made WordNet's hyponym relations.

In the future, as clues of query expansion for Peculiar Images of a target object-name, I try to utilize both its Web-extracted hyponym relations and hand-made concept hierarchies, and also both its hyponyms and appearance descriptions (e.g., color-names). In addition, I try to utilize the other appearance descriptions (e.g., shape and texture) besides color-names and the other image features besides color-features in my various Peculiar Image Retrievals.

Acknowledgments

This work was supported in part by JSPS (Japan Society for 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).

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