Query Expansion for Peculiar Images by Web-extracted Hyponyms

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***Abstract*—Most researches on Image Retrieval 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 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 images and cannot easily get exhaustive knowledge about its appearance. As next steps of Image Retrieval, 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 a novel method to search the Web for peculiar images by expanding or modifying a target object-name with its hyponyms extracted from the Web by text mining techniques, and validates its precision by comparing with Google Image Search.**

***Keywords*-image retrieval; query expansion; peculiar images; hyponymy; concept hierarchy**

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 [1] 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. 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 searches allows the user to get special images of the target object with the impression [2–4].

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" [5] which allow us to adequately figure out its typical appearance features and easily associate themselves with the correct object-name, and its "Peculiar Images" [6–8] 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 exist "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 common 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 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. 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 previous works [6], [7] have proposed a basic 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 [9], [10] and/or its peculiar image features (e.g., color-features) converted from the Web-extracted peculiar color-names. And to make the basic method more robust, my previous work [8] has proposed a refined method equipped with cross-language (translation between Japanese and English) functions like [11], [12]. As another solution, this paper proposes a novel method to search the Web for peculiar images by expanding or modifying a target object-name (of an original query) with its hyponyms extracted from the Web by using not hand-made concept hierarchies such as WordNet [13] but enormous Web documents and text mining techniques.

The remainder of this paper is organized as follows. Section II explains my proposed method for Peculiar Image Search. Section III shows several experimental results to validate its precision. Last, Section IV concludes this paper.

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II. Method

This section explains my proposed method 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 from the Web by text mining techniques.

Figure 1 gives an overview of my Peculiar Image Search (PIS) based on Web-extracted hyponym relations, while Figure 2 gives an overview of my previous Peculiar Image Search based on Web-extracted color-names [6–8].

Step 1. Hyponym Extraction

When a name of a target object as an original query is given by a user, its hyponyms are automatically extracted from exploding Web documents about the target object by text mining techniques [14], [15]. Of course, they could be extracted from hand-made concept hierarchies such as WordNet [13]. The latter is precision-oriented, while the former is rather recall-oriented. Therefore, this paper 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 PIS system collects candidates for hyponyms of a target object o by using two kinds of lexico-syntactic patterns "a * o" and "the * o" where "*" is wild-card. Next, it filters out "* o" whose frequency of Web documents searched by submitting `["` * o `"]` as a query to Google Web Search [16] is less than 10, and uses only the top 100 (at most) candidates ordered by their document frequency.

Step 2. Query Expansion by Hyponyms

Here, we have two kinds of clues to search the Web for peculiar images: 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) automatically extracted from not hand-made concept hierarchies such as WordNet but the whole Web in 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.

This paper adopts more conditioned latter to precisely search the Web for its acceptable images and "Peculiar Images".

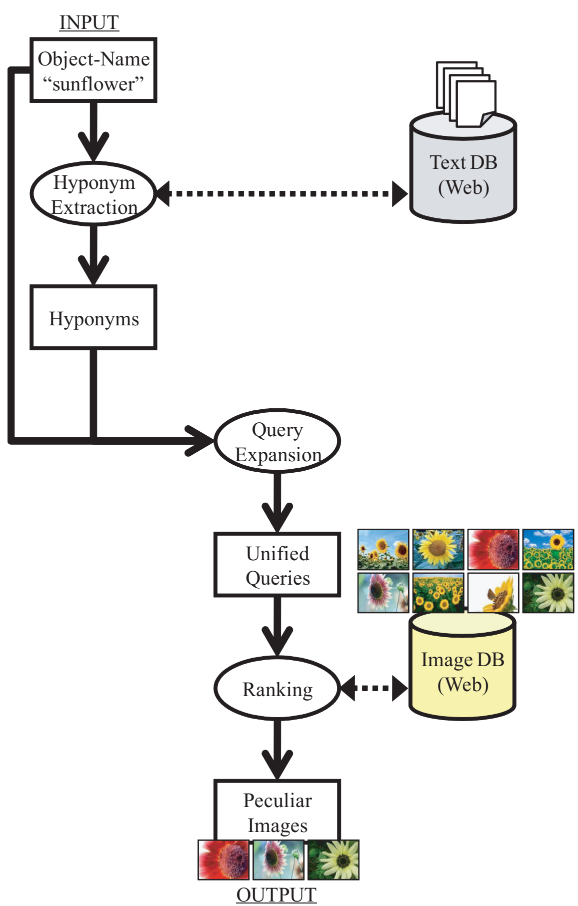

Figure 1. Peculiar Image Search based on Web-extracted Hyponyms.

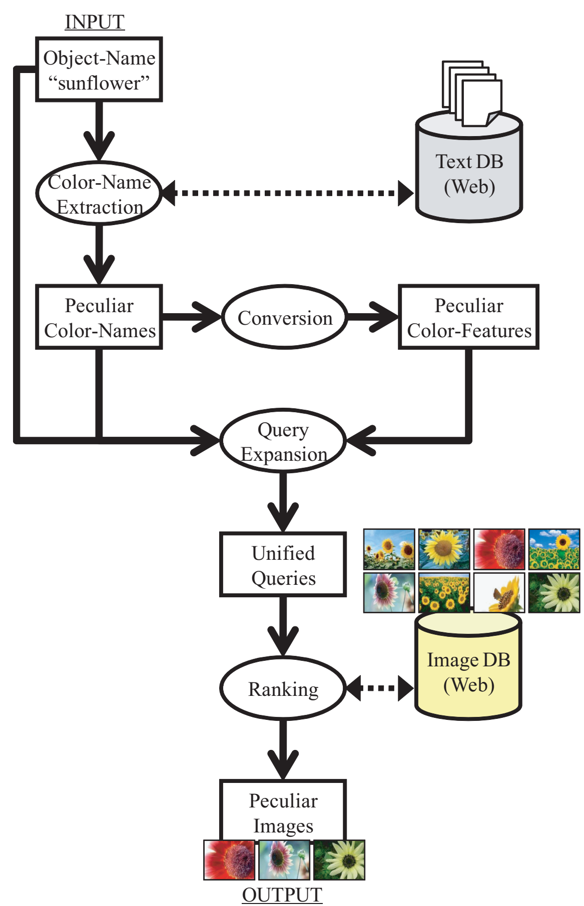

Figure 2. Peculiar Image Search based on Web-extracted Color-Names.

Step 3. Image Ranking by Expanded Queries

This paper defines two kinds of weights of Peculiar Image Search based on the expanded query (q2 = text: `["h" AND "o"]` & content: null) in Step 2.

The first weight $\mathrm{pis}_1(i,o)$ is assigned to a Web image i for a target object-name o and is defined as

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

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 Step 1, a Web image i is retrieved by submitting the text-based query `["o" AND "h"]` (e.g., `["sunflower" AND "evening sun"]`) to Google Image Search [1], and $\mathrm{rank}(i,o,h)$ stands for the rank (positive integer) of a Web image i in the retrieval 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 paper, for any hyponym candidates h of a target object-name o extracted from hand-made (so certainly precise) concept hierarchies such as WordNet, $\mathrm{hyponym}(h,o)$ is set to 1. Meanwhile, for Web-extracted hyponym candidates h of a target object-name o, $\mathrm{hyponym}(h,o)$ is calculated as,

$$\mathrm{hyponym}(h,o) := \mathrm{df}(\texttt{["}h\texttt{"]}) \;/ \max_{\forall h \in H(o)} \{\mathrm{df}(\texttt{["}h\texttt{"]})\}$$

where $\mathrm{df}(\texttt{[}q\texttt{]})$ stands for the frequency of Web documents searched by submitting a query q to Google Web Search.

The second weight $\mathrm{pis}_2(i,o)$ is assigned to a Web image i for a target object-name o and is defined as

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

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,

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

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

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

where $I_k(o)$ and $I_k(o,h)$ stand for a set of the top k (at most 100) Web images retrieved 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. And $\mathrm{sim}(i,j)$ stands for the similarity between Web images i and j in the HSV color space [17] as a cosine similarity,

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

where c stands for any color-feature in the HSV color space where 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.

III. Experiment

This section shows several experimental results for the following six kinds of target object-names to validate my proposed method to search the Web for their peculiar images more precisely than conventional Web image search engines such as Google Image Search. Table I shows the numbers of WordNet's and Web-extracted hyponyms for each object.

Table I
NUMBER OF WORDNET'S AND WEB-EXTRACTED HYPONYMS.

Object-Name	WordNet's	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 3 shows the top k average precision of my proposed Peculiar Image Searches (PIS) 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 PIS method by using the second (more refined) ranking $\mathrm{pis}_2(i,o)$ is superior to my PIS method by using the first (simpler) ranking $\mathrm{pis}_1(i,o)$ as well as Google Image Search, and that my PIS method by using Web-extracted hyponym relations is superior to my PIS method by using WordNet's ones.

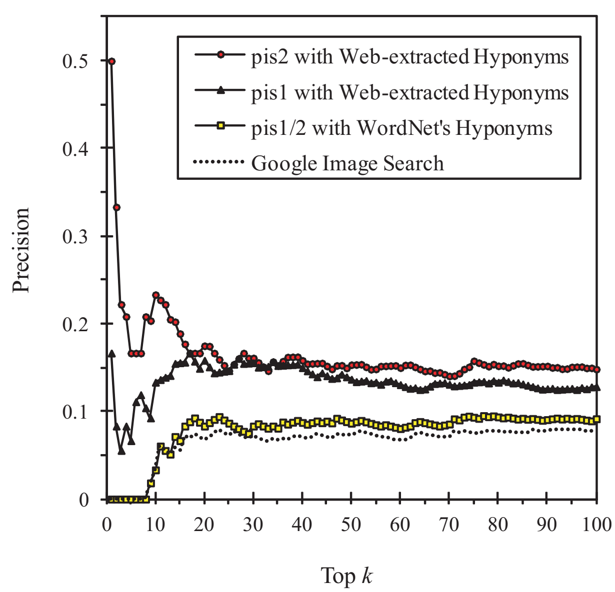

Figure 3. Top k Average Precision of Google Image Search (query: q0) vs. Peculiar Image Searches (query: q2, ranking: pis_1 or pis_2).

Table II
TOP 20 PECULIAR(-COLORED) 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

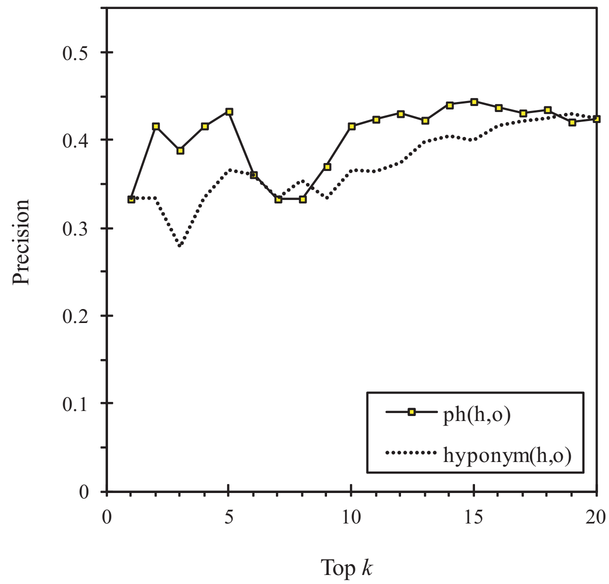

Figure 4. Top k Average Precision of Hyponym Extraction from the Web.

Table III
TOP 20 PECULIAR(-COLORED) HYPONYMS OF “CAULIFLOWER”.

	hyponym(h, o)		ph(h, o)	
1	spicy cauliflower	1000	**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

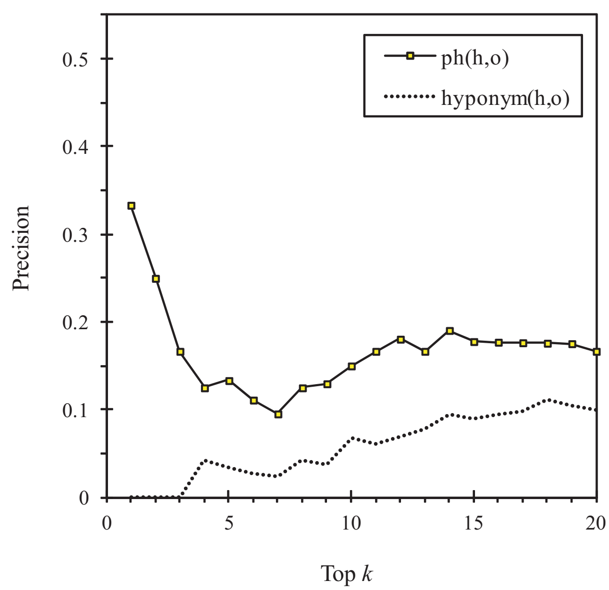

Figure 5. Top k Average Precision of Peculiar(-Colored) Hyponym Extraction from the Web.

Tables II and III show the top 20 peculiar hyponyms with peculiar color-features of a target object-name, “sunflower” and “cauliflower”, respectively. They show that ph(h, o) used by the second (more refined) ranking pis$_2(i, o)$ is superior to hyponym(h, o) used by the first (simpler) ranking pis$_2(i, o)$ as a weighting function of peculiar hyponyms h for each target object-name o. Figure 4 shows the top k average precision of hyponym extraction from the Web. ph(h, o) gives 42.5% (not much different) precision at $k = 20$ for hyponym extraction, while hyponym(h, o) gives 42.5% precision. And Figure 5 shows the top k average precision of peculiar hyponym extraction from the Web. ph(h, o) gives 16.7% (superior) precision at $k = 20$ for peculiar hyponym extraction, while hyponym(h, o) gives 10.0% precision.

Figures 6 to 11 show the top 20 search results for each target object-name, “sunflower” or “cauliflower”, to compare between Google Image Search [1] as a conventional keyword-based Web image search engine, and my proposed Peculiar Image Search by using the first (simpler) ranking function pis$_1(i, o)$ or the second (more refined) ranking function pis$_2(i, o)$ based on Web-extracted hyponym relations. They show that my proposed Peculiar Image Searches are superior to Google Image Search to search the Web for peculiar images of a target object-name.

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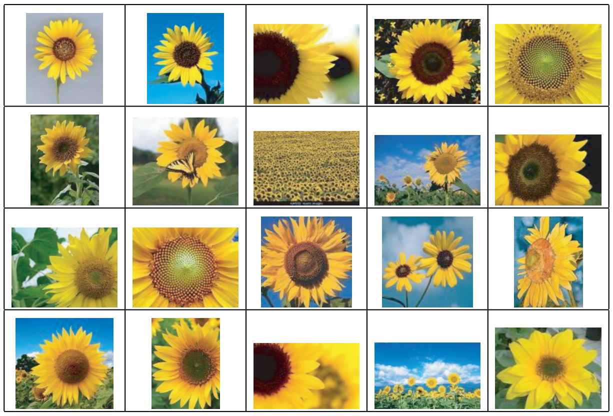

Figure 6. Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: "sunflower").

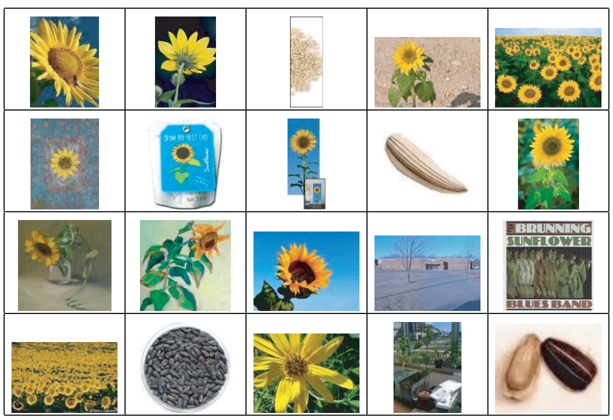

Figure 7. Top 20 results of Peculiar Image Search (query: q2, ranking: $\text{pis}_1(i, o)$, object-name: "sunflower").

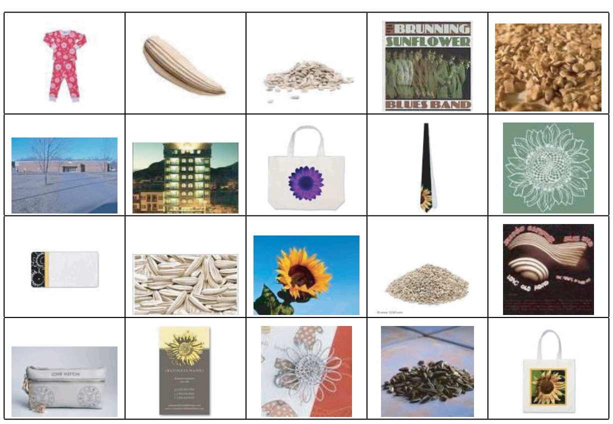

Figure 8. Top 20 results of Peculiar Image Search (query: q2, ranking: $\text{pis}_2(i, o)$, object-name: "sunflower").

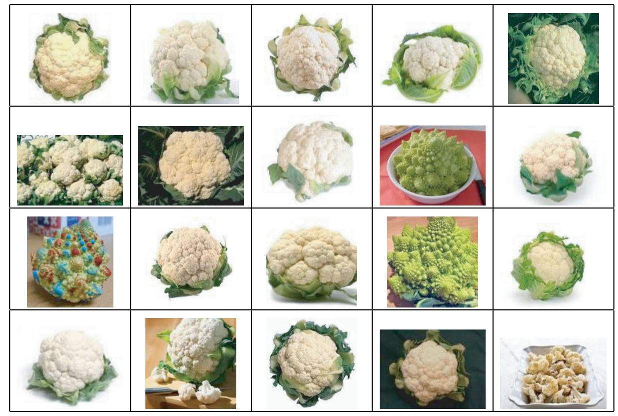

Figure 9. Top 20 results of Google Image Search (query: q0, ranking: Google, object-name: "cauliflower").

Figure 10. Top 20 results of Peculiar Image Search (query: q2, ranking: $\text{pis}_1(i, o)$, object-name: "cauliflower").

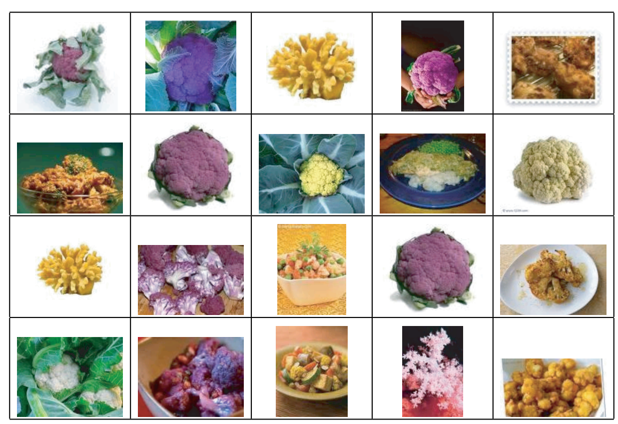

Figure 11. Top 20 results of Peculiar Image Search (query: q2, ranking: $\text{pis}_2(i, o)$, object-name: "cauliflower").

IV. Conclusion and Future Work

As next steps of Image Retrieval (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. In other words, "Exhaustiveness" is one of the most important requirements in the next IR. As a solution, my previous works proposed a basic method to precisely search the Web for peculiar images of a target object 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. And to make the basic method more robust, my previous work proposed a refined method equipped with cross-language (translation between Japanese and English) functions.

As another solution, this paper has proposed a novel method to search the Web for peculiar images by expanding or modifying a target object-name (of an original query) with its hyponyms extracted 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 show that my second (more refined) ranking $\mathrm{pis}_2(i, o)$ is superior to my first (simpler) ranking $\mathrm{pis}_1(i, o)$, and that using Web-extracted hyponym relations is superior to using hand-made WordNet's ones.

In the near 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 Searches.

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