Peculiar Image Search by Web-extracted Appearance Descriptions

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***Abstract*—We have become able to get enough approvable 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 (look and feel). As next steps of image searches in the Web, it is very important to discriminate between "Typical Images" and "Peculiar Images" in the approvable images, and moreover, to collect many different kinds of peculiar images as exhaustively as possible. This paper proposes a novel method to precisely retrieve peculiar images of a target object by its typical/peculiar appearance descriptions (e.g., color-names) extracted from the Web and/or its typical/peculiar image features (e.g., color-features) converted from them, as a solution to the 1st next step of image retrievals in the Web.**

***Keywords*-image retrieval; Web search; knowledge extraction; Web mining; query expansion; exhaustiveness;**

I. Introduction

In recent years, the Web have had enormous 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 [1] and most researches on image retrievals is to allow the user to retrieve the approvable images for the target object-name, which just include the target object in their content, as precisely as possible. However, the approvable 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 approvable 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 impressional words as additional conditions are given, allows the user to get special images of the target object with the impression [5–7].

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" [8] which allow us to figure out its typical appearance features and to associate themselves with the correct object-name easily, and its "Peculiar Images" [9], [10] 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 approvable 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 image retrievals in the Web is to clear away noisy images and search the Web for only approvable images of a target object. As next steps of image retrievals in the Web, it is very important to discriminate between "Typical Images" and "Peculiar Images" in the approvable 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 searches as well as Web document searches [11]. This paper proposes a novel method to precisely retrieve peculiar images of a target object when only its object-name as an original query is given, by refining the original query with its typical/peculiar appearance descriptions (e.g., color-names) extracted from the Web by text mining techniques [12] and/or its typical/peculiar image features (e.g., color-features) converted from the Web-extracted peculiar color-names, as a solution to the 1st next step of image retrieval. And this paper shows the effectiveness of my proposed method using not only image content analysis but also Web text mining, by comparing with VisualRank [13], [14] methods based on similarity of image features such as SIFT [15] features or HSV [16] color histograms as representatives of Content-Based Image Retrievals (CBIR) [17–22].

II. METHOD

This section explains my proposed method to precisely search the Web for "Typical Images" and "Peculiar Images" of a target object, by analyzing not only search-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.

My proposed system to search the Web for typical and peculiar images of a target object requires its object-name as only one user input, i.e., the users do not have to specify additional conditions such as its typical or peculiar appearance descriptions and/or features. Figure 1 gives an overview of my proposed Typical and Peculiar Image Searches.

Step 1. Color-Name Extraction

When a name of a target object is given by a user, its typical/peculiar color-names (as one kind of appearance descriptions) are extracted from enormous Web documents about the target object by text mining techniques [12].

The two kinds of lexico-syntactic patterns which consist of a color-name cn and the target object-name on are used:

1) "cn on", such as "yellow sunflower",
2) "on is cn", such as "sunflower is yellow".

The weight $\mathrm{tcn}(cn, on)$ of Typical Color-Name extraction is assigned to each color-name cn from among cyclopedic 632 ones [3] for a target object-name on as follows:

$$\mathrm{tcn}(cn, on) := \mathrm{df}(\texttt{["}cn\ on\texttt{"]}) \cdot \mathrm{df}(\texttt{["}on \text{ is } cn\texttt{"]}),$$

where $\mathrm{df}(\texttt{["}q\texttt{"]})$ stands for the frequency of Web documents retrieved by submitting the phrase query "q" to Google Web Search [2]. The color-name assigned with the biggest typicality is adopted as the typical color-name cn_t of the target object-name on.

Meanwhile, the weight $\mathrm{pcn}_x(cn, on)$ of Peculiar Color-Name extraction is assigned to each color-name cn from among cyclopedic 632 ones [3] as follows:

$$\mathrm{pcn}_{632}(cn, on) := \begin{cases} 0 & \text{if } \mathrm{df}(\texttt{["}on \text{ is } cn\texttt{"]}){=}0, \\ \dfrac{\mathrm{df}(\texttt{["}cn\ on\texttt{"]})}{\mathrm{df}(\texttt{["}on \text{ is } cn\texttt{"]}){+}1} & \text{otherwise.} \end{cases}$$

And another weight of peculiar color-name extraction is assigned to each of only 11 basic color-terms in English [4], C_{11} = {"black", "white", "red", "green", "yellow", "blue", "brown", "orange", "pink", "purple", "gray"}, as follows:

$$\mathrm{pcn}_{11}(cn, on) := \begin{cases} 0 & \text{if } cn \notin C_{11}, \\ \dfrac{\mathrm{df}(\texttt{["}cn\ on\texttt{"]})}{\mathrm{df}(\texttt{["}on \text{ is } cn\texttt{"]}){+}1} & \text{otherwise.} \end{cases}$$

The color-names assigned with higher peculiarity than $\mathrm{pcn}_x(cn_t, on)$, which is the peculiarity of the typical color-name cn_t, are adopted as the peculiar color-name cn_p of the target object-name on.

Step 2. Color-Feature Conversion

The typical/peculiar HSV color space values cf_t or cf_p (as one kind of image features) of the target object are converted from its Web-extracted typical/peculiar color-names cn_t or cn_p by referring the conversion table [3] respectively.

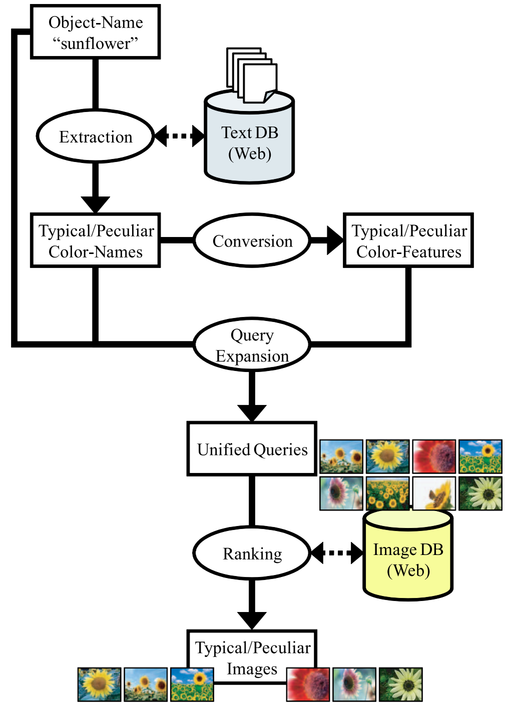

Figure 1. Overview of Typical and Peculiar Image Searches

Step 3. Query Expansion

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

The original query (q0 = text: $\texttt{["}on\texttt{"]}$ & content: null) can be expanded by its typical/peculiar color-names cn_y and/or its typical/peculiar color-features cf_y as follows:

q1	= text: $\texttt{["}on\texttt{"]}$ & content: cf_y,
q2	= text: $\texttt{["}cn_y\ on\texttt{"]}$ & content: null,
q2a	= text: $\texttt{["}on\texttt{" AND "}cn_y\texttt{"]}$ & content: null,
q3	= text: $\texttt{["}cn_y\ on\texttt{"]}$ & content: cf_y,
q3a	= text: $\texttt{["}on\texttt{" AND "}cn_y\texttt{"]}$ & content: cf_y.

Step 4. Image Ranking by Expanded Queries

The weight $\mathrm{tis}(i, on)$ of Typical Image Search is assigned to a Web image i for a target object-name on and is defined as how much the image i contains the similar color-features to its typical color-feature cf_t in the content:

$$\mathrm{tis}(i, on) := \mathrm{cont}(i, cf_t),$$

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

where a Web image i is retrieved by submitting the text-based query `["`on`"]`, `["`cn_t on`"]`, or `["`on`" AND "`cn_t`"]` (e.g., `["sunflower"]`, `["yellow sunflower"]`, or `["sunflower" AND "yellow"]`) to Google Image Search [1], $\mathrm{sim}(cf, cf_y)$ stands for the similarity between color-features cf and cf_y in HSV color space [16], and $\mathrm{prop}(cf, i)$ stands for the proportion of a color-feature cf in an image i.

Meanwhile, the weight $\mathrm{pis1}(i, on)$ of Peculiar Image Search based on the 1st type of expanded query (q1 = text: `["`on`"]` & content: cf_p) is assigned to a Web image i for a target object-name on and is defined as follows:

$$\mathrm{pis1}(i, on) := \max_{\forall(cn_p, cf_p)} \Big\{ \mathrm{pcn}_x(cn_p, on) \cdot \mathrm{cont}(i, cf_p) \Big\},$$

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 in the Step 2.

Next, the peculiarity of a Web image i for a target object-name on, based on the 2nd type of expanded query (q2 = text: `["`cn_p on`"]` & content: null, or q2a = text: `["`on`" AND "`cn_p`"]` & content: null), is defined as follows:

$$\mathrm{pis2}(i, on) := \max_{\forall cn_p} \left\{ \frac{\mathrm{pcn}_x(cn_p, on)}{\mathrm{rank}(i, on, cn_p)^2} \right\},$$

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 $\mathrm{rank}(i, on, cn_p)$ stands for the rank of a Web image i in the retrieval results by submitting the text-based query `["`cn_p on`"]` or `["`on`" AND "`cn_p`"]` to Google Images.

Third, the peculiarity of a Web image i for a target object-name on, based on the 3rd type of expanded query (q3 = text: `["`cn_p on`"]` & content: cf_p, or q3a = text: `["`on`" AND "`cn_p`"]` & content: cf_p), is defined as follows:

$$\mathrm{pis3}(i, on) := \max_{\forall(cn_p, cf_p)} \left\{ \frac{\mathrm{pcn}_x(cn_p, on) \cdot \mathrm{cont}(i, cf_p)}{\mathrm{rank}(i, on, cn_p)} \right\},$$

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 in the Step 2.

Last, the peculiarity (in color) of a Web image i for a target object-name on, based on its typical color as well as its peculiar color(s), is defined as follows:

$$\mathrm{pis1t}(i, on) := \mathrm{pis1}(i, on) \cdot f(\mathrm{tis}(i, on)),$$

$$\mathrm{pis2t}(i, on) := \mathrm{pis2}(i, on) \cdot f(\mathrm{tis}(i, on)),$$

$$\mathrm{pis3t}(i, on) := \mathrm{pis3}(i, on) \cdot f(\mathrm{tis}(i, on)),$$

where $f(t)$ stands for such a monotonically decreasing function in [0,1] as the Normal distribution function:

$$f(t) := N(0, \sigma, t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{t^2}{2\sigma^2}\right),$$

where σ is set to $1/\sqrt{2\pi}$ to meet $f(0) = N(0, \sigma, 0) = 1$.

III. Experiment

This section justifies the effectiveness of my proposed method to search the Web for typical/peculiar images by showing several experimental results.

First, the experimental results of my proposed method to extract typical/peculiar color-names from the Web for such a target object-name as "sunflower", "cauliflower", and "Tokyo tower" (the Step 1 of Section 2) are shown. Table I shows the top k results of the Web-extracted typical/peculiar color-names for a target object-name on = "sunflower". The method can extract the approvable typical color-name from the Web for each of three kinds of target object-names on the top 1: "yellow" for "sunflower", "white" for "cauliflower", and "red" for "Tokyo tower". And the method seems to be able to extract the approvable peculiar color-names for each of three kinds of target object-names by using the weighting function $\mathrm{pcn}_{632}(cn, on)$, but also assign high weight to some noisy color-names. These noisy color-names might be harmful effects in the precision throughout the whole method (the Steps 1 - 4 of Section 2) of my proposed Peculiar Image Searches.

Second, the experimental results of my proposed method to search the Web for peculiar images (the Steps 1 - 4 of Section 2) are shown. Table II compares the top k ($\in \{20, 40, 60, 80, 100\}$) precision and the area under the precision curve between Google Image Search, VisualRank methods based on similarity of image features such as SIFT features or HSV color histograms. Among 23 methods, my proposed method of peculiar image search based on query expansion by Web-extracted peculiar color-names from 11 basic color terms in English and using not only the peculiarity $\mathrm{pis3}(i, on)$ but also the typicality $\mathrm{tis}(i, on)$ of each Web image i for a target object-name on gives the best performance. Also, Table II and Figures 2 and 3 show that

- in the Step 1 of Section 2, peculiar color-name extraction from 11 basic color terms in English gives better performance than from cyclopedic 632 ones,
- in the Step 3, as text-based condition(s), the usage of `["`cn_p on`"]` gives worse performance than the usage of `["`on`" AND "`cn_p`"]`, i.e., q2 < q2a and q3 < q3a,
- in the Step 3, the usage of peculiar color-features cf_p gives worse performance, i.e., q3 < q2 and q3a < q2a,
- in the Step 4, the usage of $f(\mathrm{tis}(i, on))$ gives better performance, i.e., $\mathrm{pis1}(i, on) < \mathrm{pis1t}(i, on)$, $\mathrm{pis2}(i, on) < \mathrm{pis2t}(i, on)$ and $\mathrm{pis3}(i, on) < \mathrm{pis3t}(i, on)$.

Next, Figures 4 - 6 show the top 20 search results for a target object-name, "sunflower", to compare between Google Image Search, VisualRank method based on similarity of HSV color histograms, and the best of my proposed Peculiar Image Searches ($\mathrm{pis2t}(i, on)$, 11 colors, q2a = text: `["`on`" AND "`cn_p`"]` & content: null). PIS can retrieve 15 peculiar images of different colors of sunflowers, while GIS and iVR+HSV can retrieve one of only red-brown sunflowers.

Table I
WEB-EXTRACTED TYPICAL/PECULIAR COLOR-NAMES OF OBJECT-NAME on = "SUNFLOWER".

	df(["cn on"])			df(["on is cn"])			Typical Color-Name tcn(cn, on)			Peculiar Color-Name pcn$_{632}$(cn, on)			Peculiar Color-Name pcn$_{11}$(cn, on)	
1	pumpkin	947	1	yellow	44	**1**	**yellow**	**26356**	**1**	**gold**	**368.0**	**1**	**orange**	**736.0**
2	almond	945	2	golden brown	13	2	black	5052	**2**	**desert**	**324.0**	**2**	**gray**	**273.0**
3	flax	890	3	yellow-green	11	3	red	3224	**3**	**chocolate**	**311.0**	**3**	**purple**	**232.0**
4	olive	882	4	tan	10	4	tan	2410	**4**	**silver**	**302.0**	**4**	**green**	**204.0**
5	wheat	848	5	black	6	5	rose	2199	**5**	**purple**	**232.0**	**5**	**pink**	**184.7**
6	black	842	6	brown	5	6	blue	2055	**6**	**green**	**204.0**	**6**	**blue**	**171.3**
7	red	806	6	light brown	5	7	brown	2035	**7**	**bronze**	**200.5**	**7**	**red**	**161.2**
8	gold	736	8	red	4	8	white	1770	**8**	**pink**	**184.7**	**8**	**white**	**147.5**
9	orange	736	9	blue	3	9	green	1224	**9**	**rose**	**183.3**	**9**	**black**	**120.3**
10	rose	733	9	white	3	10	pink	1108	**10**	**blue**	**171.3**	**10**	**brown**	**67.8**
	:			:			:			**:**		11	yellow	13.3
									24	**bittersweet**	**21.5**			
19	yellow	599							25	yellow	13.3			

Table II
AVERAGE PRECISION IN THE TOP k AND AREA UNDER THE PRECISION CURVE OF PECULIAR IMAGE SEARCHES.

Search Method	Top 20	Top 40	Top 60	Top 80	Top 100	Area
Google Image Search	0.11666	0.13333	0.13333	0.13333	0.12666	12.6633
inverted VisualRank+SIFT	0.10000	0.13333	0.11111	0.13750	0.12666	12.4581
inverted VisualRank+HSV	0.23333	0.20000	0.17222	0.14166	0.12666	19.2874
pis1(i, on), 632 colors, q1	0.05000	0.07500	0.10000	0.10833	0.12666	9.7365
pis2(i, on), 632 colors, q2	0.38333	0.39166	0.32777	0.35416	0.34333	34.8043
pis2(i, on), 632 colors, q2a	0.46666	0.40833	0.38888	0.34166	0.31333	38.3004
pis3(i, on), 632 colors, q3	0.36666	0.27500	0.26666	0.25416	0.24666	27.5666
pis3(i, on), 632 colors, q3a	0.21666	0.24166	0.21666	0.21666	0.21000	22.0431
pis1(i, on), 11 colors, q1	0.01666	0.05000	0.07777	0.11250	0.12666	6.1712
pis2(i, on), 11 colors, q2	0.42105	0.39166	0.36111	0.37083	0.35000	36.9513
pis2(i, on), 11 colors, q2a	0.50000	0.43333	0.38888	0.36250	0.33666	41.1292
pis3(i, on), 11 colors, q3	0.33333	0.31666	0.27777	0.27500	0.25333	30.2754
pis3(i, on), 11 colors, q3a	0.38333	0.29166	0.26111	0.23750	0.24000	32.1945
pis1t(i, on), 632 colors, q1	0.20000	0.15000	0.13888	0.14583	0.12666	16.0461
pis2t(i, on), 632 colors, q2	0.43333	0.39166	0.34444	0.37083	0.36000	36.3779
pis2t(i, on), 632 colors, q2a	0.50000	0.44166	0.41666	0.36666	0.33666	41.1963
pis3t(i, on), 632 colors, q3	0.40000	0.34166	0.30000	0.31250	0.28666	31.8273
pis3t(i, on), 632 colors, q3a	0.25000	0.25833	0.22222	0.22916	0.23000	23.4949
pis1t(i, on), 11 colors, q1	0.20000	0.15000	0.13888	0.14583	0.12666	16.0461
pis2t(i, on), 11 colors, q2	0.45000	0.39166	0.37222	0.38750	0.37666	38.7887
pis2t(i, on), 11 colors, q2a	**0.53333**	**0.48333**	**0.44444**	**0.40000**	**0.38333**	**45.4334**
pis3t(i, on), 11 colors, q3	0.40000	0.35833	0.31666	0.30833	0.31666	34.9392
pis3t(i, on), 11 colors, q3a	0.43333	0.33333	0.28333	0.28750	0.28666	35.6185

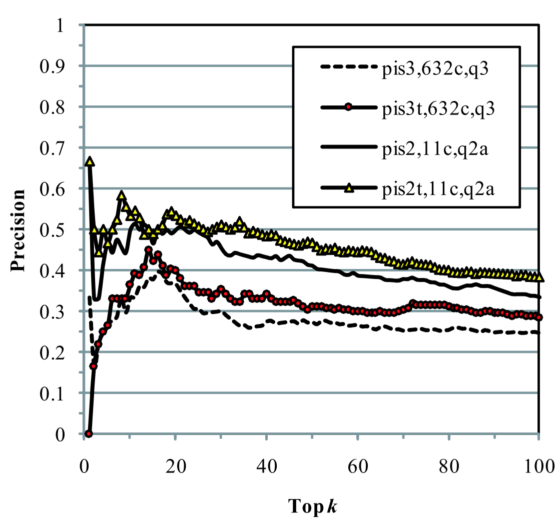

Figure 2. Top k average precision of Peculiar Image Searches: pis2/3 vs. pis2/3t, i.e., effect of f(tis(i, on)).

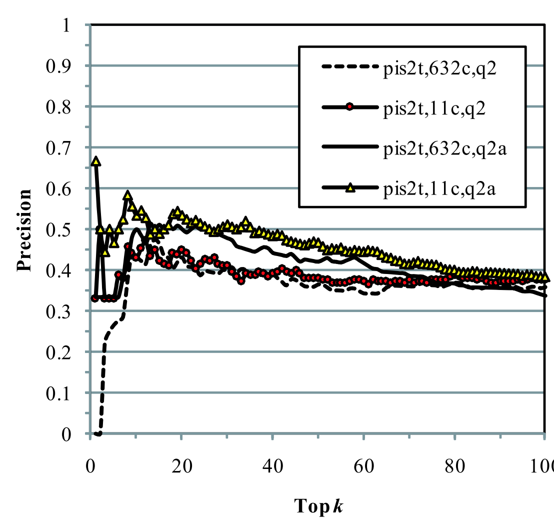

Figure 3. Top k average precision of Peculiar Image Searches: 632 vs. 11 colors, and q2 ["cn_p on"] vs. q2a ["on" AND "cn_p"].

Figure 4. Google Image Search (object-name on = "sunflower").

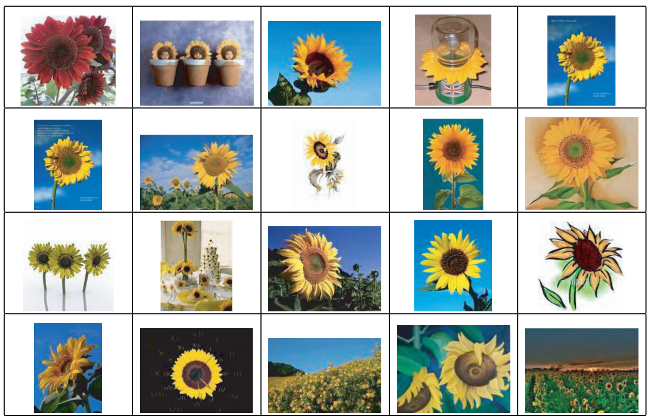

Figure 5. Inverted VisualRank+HSV (object-name on = "sunflower").

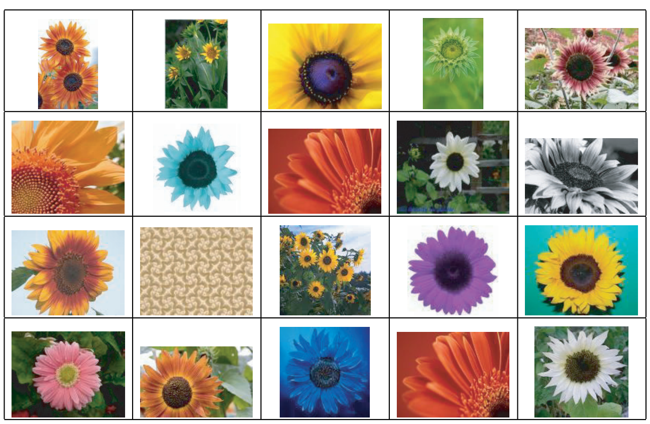

Figure 6. Peculiar Image Search (object-name on = "sunflower")

Last, Figures 7 and 8 show the top k average precision and recall (number of peculiar colors) curves of the top k search results for peculiar images respectively, to compare the best of my proposed Peculiar Image Searches with Google Image Search and VisualRank methods based on similarity of image features such as SIFT features or HSV color histograms. The best of my proposed Peculiar Image Searches is much superior to the other methods with regard to not only the top k average precision but also the top k average recall. Originally, my proposed method to search the Web for typical and peculiar images is designed as a solution to the 1st next step of Web image searches, i.e., to discriminate between "Typical Images" and "Peculiar Images" in the approvable images. Fortunately, my proposed method is better as a solution to the 2nd next step of Web image searches, i.e., to collect many different kinds of peculiar images as exhaustively as possible.

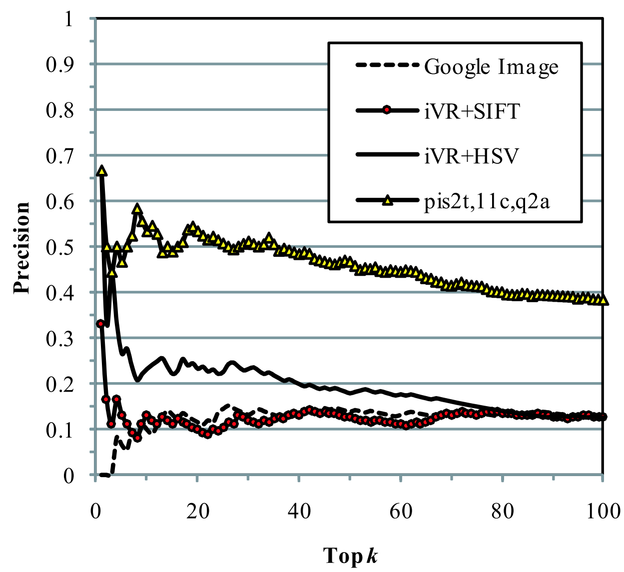

Figure 7. Top k average precision of Google Image Search, inverted VisualRank+SIFT, inverted VisualRank+HSV, and the best of my proposed Peculiar Image Search.

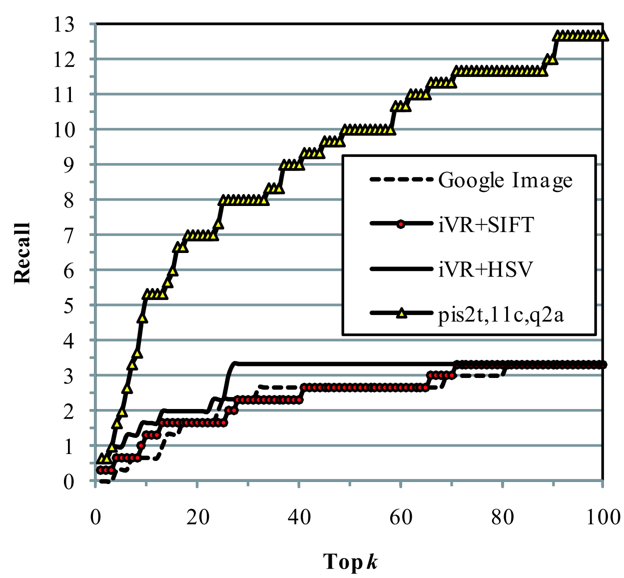

Figure 8. Top k average recall (number of peculiar colors) of Google Image Search, inverted VisualRank+SIFT, inverted VisualRank+HSV, and the best of my proposed Peculiar Image Search.

IV. Conclusion

As next steps of image searches in the Web, it is very important to discriminate between "Typical Images" [8] and "Peculiar Images" [9], [10] in the approvable images, and moreover, to collect many different kinds of peculiar images as exhaustively as possible, i.e., "Exhaustiveness" is one of the most important requirements in the next-generation Web image retrievals as well as Web document retrievals.

This paper has proposed a novel method to precisely retrieve peculiar images of a target object by its peculiar color-names (text) extracted from the Web [12] and/or color-features (image) converted from them, as a solution to the 1st next step of image retrieval. And the experimental results have showed the effectiveness of my proposed method using not only image content analysis but also Web text mining, by comparing with VisualRank methods based on similarity of image features such as SIFT features or HSV color histograms. They have showed that my proposed Peculiar Image Search is much superior to the other methods with regard to not only the top k average precision but also the top k average recall (number of peculiar colors) and makes a significant contribution to "Exhaustiveness" of retrieval results in the context of Web image searches.

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