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Article

Using Multi-Descriptors for Real Time Cosmetic Image Retrieval

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Abstract. Cosmetic Image Retrieval (CIR) is a methodology for searching and retrieving images from Cosmetic Image Collection (CIC). There are numerous cosmetic brands whose types are similar to others. In addition, there are not trivial to retrieve cosmetic images because of its complexity and duplicative shape, as well as detail of various cosmetic items. We present a method for CIR using multi-descriptors, combining global and local features for image descriptors. Along with integrating a Scale-Invariant Feature Transform (SIFT) and Critical Point Filters (CPFs) to achieve accuracy and agility in CIR processing, called CPF level 9 & SIFT. SIFT is used for detailed-image, such as cosmetic image, to reduce the time complexity for extracting keypoints. On the other side, CPF will filter only for the critical pixel of the image. From the experiment, our method can reduce computation time by 50.46% and 99.99% by using SIFT and CPF respectively. Moreover, our method is preserved efficiency, measured by precision and recall of CPF level 9 & SIFT, which is as high as the precision and recall of SIFT.

Keywords: Image retrieval, scale-invariant feature transform, critical point filters, cosmetic.

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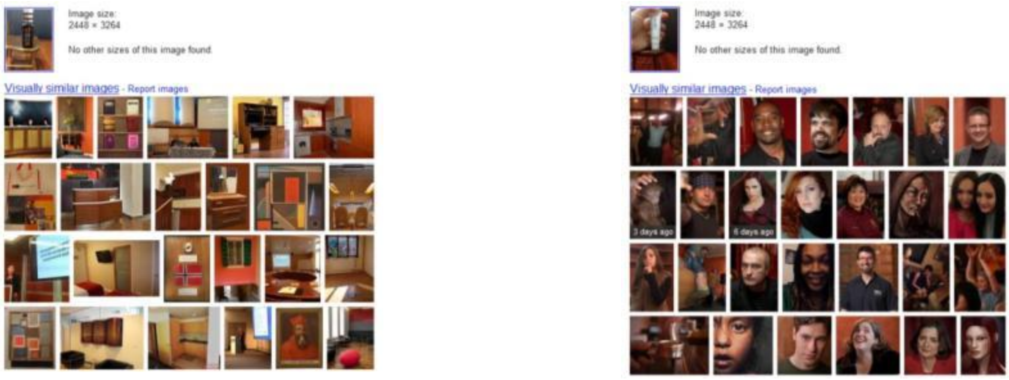
1. Introduction

There are numerous cosmetic brands around the world and each cosmetic brand has a lot of in-brand items. That will cause cosmetic customers confused easily by the similarity of the shape of cosmetic containers, color and type of in-brand products.

Cosmetic image retrieval is a method of searching and retrieving cosmetic image from image collection. There are numerous of search engines; such as Google™ and Yahoo!® that can retrieve image by using textual descriptors or by using image as an input. Due to Google™ is generic image search for web image and not specific to cosmetic images search, Google™ will not retrieve cosmetic image. After input cosmetic images to Google™, we retrieved the images of rooms and furniture as shown in Fig. 1(a) and retrieved the images of human faces as shown in Fig. 1(b).



(a) (b)

Fig. 1. Cosmetic image retrieval by using image as an input from Google™.

Then, we search cosmetic images from Google™ by using textual descriptors. According to Fig. 2, we have to input many keywords and details to get the correct cosmetic image. Furthermore, if the cosmetic items have details in others languages that we do not know, we cannot use textual descriptor for searching as shown in Fig. 3.

Due to the inconvenience of using textual descriptions in cosmetic image retrieval as mentioned above, content-based image retrieval (CBIR) is used to represent an image similarity from visual content instead [1]. However, there is still one open problem with CBIR, it is hard to achieve the satisfactory in evaluating the efficiency of visual similarity and semantic similarity.

There are various proposed solutions for image retrieval which is using descriptors to describe the details of image. For example, image segmentation, pyramid histogram of oriented gradient and critical point filters. All solutions have the strong points and weak points which trade-off between speed and accuracy. Thus, our research will find how to combine various descriptors in cosmetic image retrieval for decreasing computing time while preserving accuracy.

2. Literature Review

CBIR technology has been wildly used in real-world, numerous methods and techniques have been adopted to provide the powerful image retrieval system such as image segmentation [2], pyramid histogram of oriented gradient [3, 4] and critical point filters [1]. Major types of features is one of the CBIR. Major types of features can be divided into global features and local features. Global features are color features, texture features and shape features. Local feature is salient points [1].

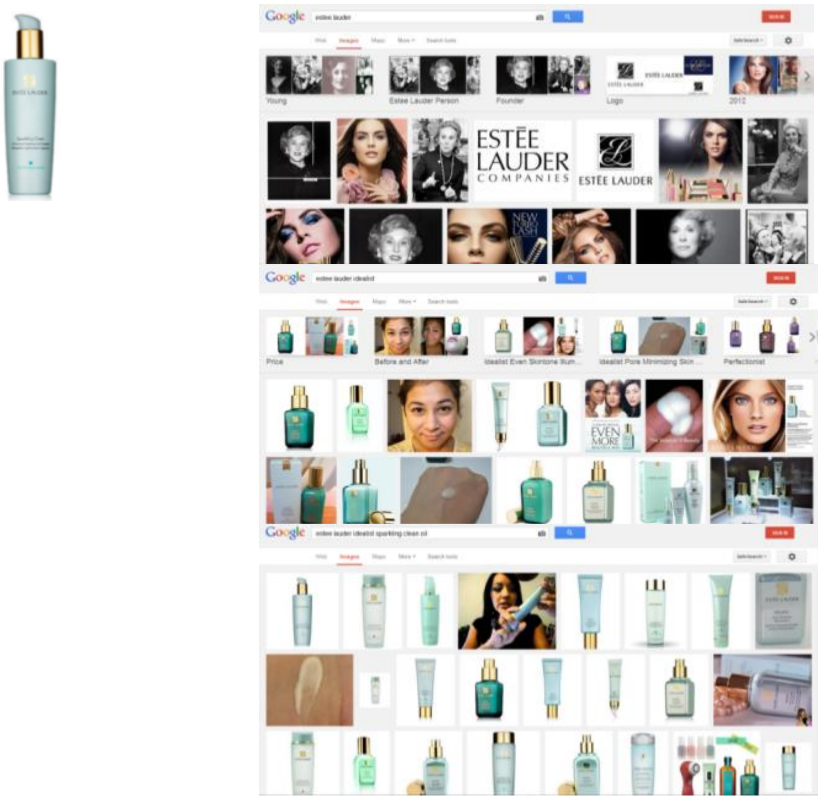
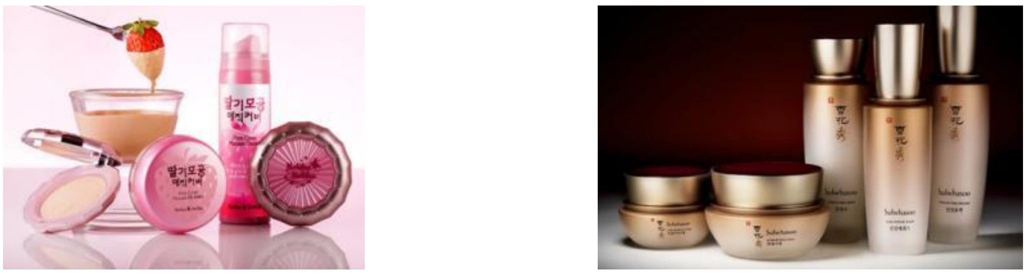


Fig. 2. Cosmetic image retrieval by textual description from Google™; on the left side is the cosmetic image which will be retrieved; on the right side from top to bottom are added more keywords until getting the correct result.



(a) (b)

Fig. 3. Examples of cosmetic image in other languages.

2.1. Global Feature

The first global feature is color feature [5–7]. This feature will divide the image into small sub-image and compute all the pixels by using its neighbour pixels. According to Fig.4(a) and4(b), cosmetic image retrieval cannot use only color feature to classify the brand and type of cosmetic image correctly because each cosmetic item can have similar color that make the classification do not give the satisfactory result.

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Fig. 4. An example of cosmetic items which are similar in color, texture and shape.

The next feature is texture feature which is often used in the repeated form of surface of image such as fur of animal, field and grass in the lawn [1]. From Figs. 4(a) - 4(d), the texture of cosmetic items are very similar to each other. Hence, texture feature is not suitable for cosmetic image retrieval.

The last global feature is shape feature. Shape feature is effective and reliable for matching shape similarity between two images. However, for cosmetic image retrieval, only shape feature cannot classify cosmetic item correctly due to the similarity of cosmetic item's shape as shown in Fig. 4(d).

In our research, we represent critical point filters (CPFs) as global feature. The reason is that CPFs is a method that filter the prominent pixels of image by using color feature, texture feature and shape feature into image pyramid hierarchies.

2.2. Local Feature

Local feature is salient point which is the outstanding point of image. Salient point is based on local invariant feature and the proficiency of salient point in cosmetic image retrieval is not decreased by scale, translation, rotation and illumination changes. Furthermore, salient point can classify brand and type of cosmetic by using interest points matching.

In our research, we represent scale-invariant feature transform (SIFT) as local feature [8–12]. SIFT use image key to identify the candidate object matching between a pair of images [13–15] as shown in Fig. 5.

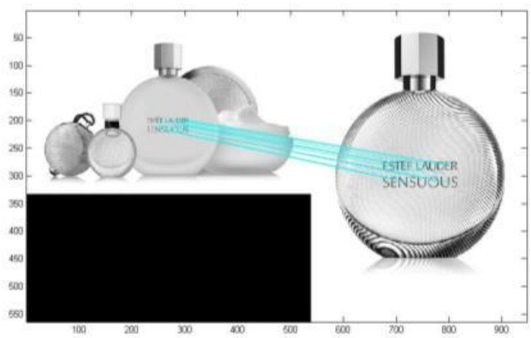

Fig. 5. An example of SIFT keypoint matching in cosmetic image.

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2.3. Conclusion

In conclusion, we will combine four major types of feature together. Critical point filters (CPFs) is represented as global feature which consists of color feature, texture feature and shape feature [16–22]and scale invariant feature transform (SIFT) is represented as local feature.

3. Methodology

The algorithm of real time cosmetic image will use two descriptors. The first descriptor is global feature; critical point filters (CPFs), which will extract the prominent features of the image into image pyramid hierarchies. Another feature is local feature; scale invariant feature transform (SIFT), which could extract the descriptor feature from one hierarchy of global feature extracted image pyramid without disturbing by scaling, translation, rotation, illumination change or 3D projection.

In our methodology, brand is the symbol of one cosmetic brand name which consists of brand name or logo or both as shown in Fig. 6 and in-brand or type is the cosmetic product in each brand that consists of the information and details of the product as shown in Table 1.

The steps of cosmetic image retrieval diagram are shown in Fig. 7. In the step of matching image to image collection is divided into brand classification and type classification. First, we provide brand classification for classifying the brand of cosmetic. Then, we provide in-brand classification for classifying in-brand (type) and retrieve the exact cosmetic image in that brand as shown in Fig. 9.

Furthermore, keypoint descriptor method diagram is shown in Fig. 8. From the diagram, to extract the interest points in scale-space extrema detecting step, we apply SIFT and CPFs together. CPFs can filter the prominent points from the image which help reducing the amount of SIFT's interest points.

To provide the image pyramid hierarchy, the input image must be pre-processed into $2^n x 2^n$ pixels. Higher level of image pyramid hierarchy has less computation than lower level of image pyramid hierarchy. However, the speed in computation is trade-off with accuracy. Thus, in order to find the most suitable CPF hierarchy level of image pyramid which give the best solution when applying with SIFT. We had to determine in the experiment. Our method can be categorized into three major steps.

Fig. 6. Examples of brand (brand name and logo).

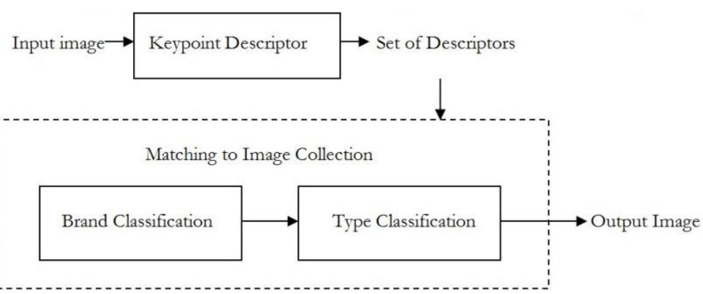


Fig. 7. A diagram of cosmetic image retrieval method.

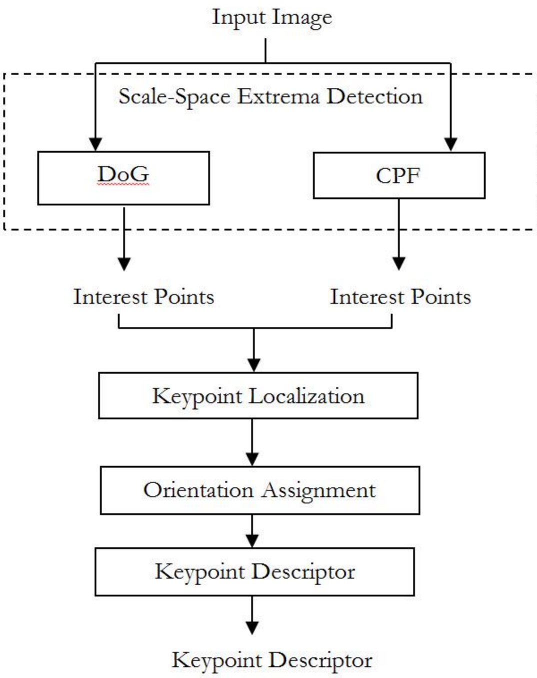


Fig. 8. A diagram of keypoint descriptor method.

Table 1. Example of in-brand or type of cosmetic items in one brand.

Brand	In-Brand (Type)
雪肌精 SEKKISEI KOSÉ	
NIVEA	
L'ORÉAL PARIS	
THE BODY SHOP	
ESTĒE LAUDER	

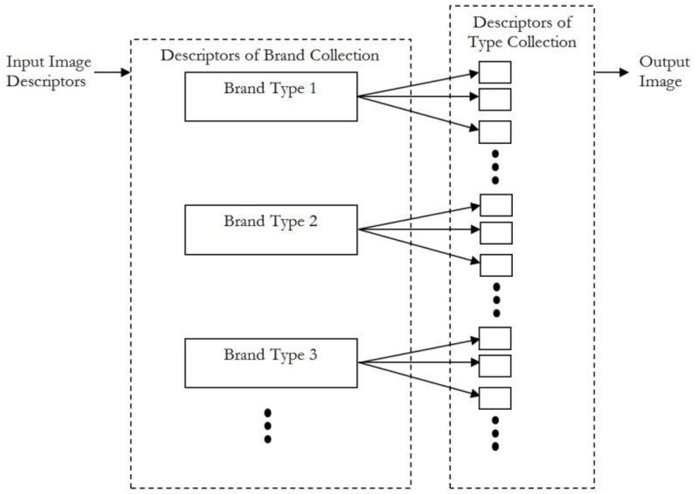


Fig. 9. A diagram of image collection.

3.1. Extract Interest Points

To extract interest points, we combine CPF and SIFT. First, we provide the image pyramid hierarchy by CPF to get the CPF critical points or prominent points and provide SIFT to get SIFT interest points. The duplicate interest points of CPF critical points and SIFT interest points will decrease the total amount of interest points that will be used next. The interest points reduction will reduce the computation and processing time in the next steps.

3.1.1. Hierarchies of critical point filters

Critical point filters (CPFs) can filter the critical points or prominent features of input image ($2^n x 2^n$ pixels) by considering from color, texture and shape and build image pyramid as shown in Fig.10.The main prominent features of input image are still preserved in the different levels of pyramid hierarchy after extracting. We also compare the different interest points detected from SIFT and from CPF at different level in Table 2.

Fig. 10. On the left side is 4096x4096($2^{12}x2^{12}$) pixels of input cosmetic Image. On the right side are images from different hierarchy of image pyramid.

Table 2. The different interest points detected from SIFT and from CPF at different level.

Level of Hierarchy	Average CPF Interest Points (points)	Average SIFT Interest Points (points)
6	2^6x2^6	42.17
7	2^7x2^7	159.8
8	2^8x2^8	235.7
9	2^9x2^9	413.2
10	$2^{10}x2^{10}$	1915
11	$2^{11}x2^{11}$	9047
12	$2^{12}x2^{12}$	37363

3.1.2. Scale-Space Extrema

After getting the critical points from previous step, we compute the difference-of-Gaussian (DoG) of image and extract SIFT interest points by detecting local extrema. The consistent interest points of CPF critical points and SIFT interest points decreases the amount of total interest points that will be used in the next steps.

3.2. Keypoint Descriptor Detection

According to Fig. 8, after getting the consistent interest points from previous steps, a diagram shows the step of keypoint detection method. In this step, we assign the orientation and provide keypoint descriptors.

3.2.1. Keypoint Localization

The next step is determining the location for each candidate keypoint. We interpolate nearby data to get the accurate position by using quadratic Taylor expansion of DoG scale-space function.

3.2.2. Orientation Assignment

To assign orientation to keypoint, we use local image gradient directions. For one keypoint, we can assign one or more orientations.

3.2.3. Keypoint Descriptor

Next is the step of computing keypoint descriptor. In this step, we provide image closest in scale to the scale of keypoint to obtain each keypoint descriptor vector. This keypoint descriptor vector is invariant and highly distinctive.

3.3. Keypoint Matching

From Fig. 9, we have to provide brand classification by matching descriptors of input image to descriptors of cosmetic brand collection. After classifying the cosmetic brand, the descriptors of cosmetic brand will be deleted from the descriptors of input images Then, matching the remaining descriptors with the descriptors of type collection with the same brand name.

4. Experiment Result

In the experiment, we perform 3 algorithms which are CPF, SIFT and CPF&SIFT. All 3 algorithms follow the same steps as mentioned in previous section. After obtaining the retrieved images from each algorithm, we compute precision and recall [23]. Then, we compare them to measure the efficiency of each algorithm. Moreover, we also compare the computation time of CPF, SIFT and CPF&SIFT to measure the computational efficiency.

The experimental result is shown in 3 topics: varying the hierarchy in the cosmetic image pyramid, matching the cosmetic image to the cosmetic image database, and matching small part cutting of image.

4.1. Varying Hierarchy in Cosmetic Image Pyramid

We find the matching points of cosmetic images at different hierarchies of the image pyramid. We use CPF to obtain the image pyramid and then use SIFT to find the matching points and the result is shown in Table 3 and Fig. 11.

This experiment starts from image pyramid hierarchy at level 6 because the lower level is too small for SIFT to provide the octave of scale-space and ends at image pyramid hierarchy level 12 because the results that shown in Fig. 11 are nearly stable compare to level 10 and level 11. According to Table 3 and Fig. 11, image pyramid hierarchy at level 9 give the best result. Even the result at level 9 is slower processing compared to the result at hierarchy level 8 and below but it is more accurate. On the other hand, although the precision and recall of hierarchy level 10, level 11 and level 12 are the highest, the computation time is increased from hierarchy level 9 by 116.8%, 220.1% and 320.0% in order. Hence, CPF of image pyramid hierarchy at level 9 will be used for our cosmetic image retrieval in the next experiment.

Table 3. Result of cosmetic images at different hierarchy.

Level of Hierarchy	Average Time (s)	Average Time Increase/Decrease (%)	Average Matching Points (points)	Average Matching Points Increase (%)
6	0.059	-	5.83	-
7	0.070	18.6	25.2	332
8	0.082	17.1	46.5	84.5
9	0.101	23.2	187	302
10	0.219	116.8	349	86.6
11	0.701	220.1	1326	278
12	2.944	320.0	5165	290

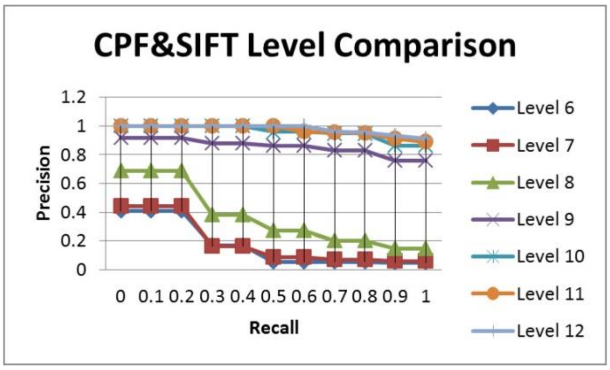


Fig. 11. Precision and recall diagram of each CPF&SIFT level comparison.

4.2. Matching the Cosmetic Image to Database

We categorize this section into 2 sections as brand classification and type classification. Our method starts with brand classification and then provides type classification.

From observing cosmetic brand, we can classify cosmetic brand into 5 main brand types. The details of each brand types are shown in Table 4.

In image collection, there are 100 images which are divided into 5 brand types and each brand type has 20 images and all the images have black background as shown in Table 5. From Table 6, there are 3 test sets, each test set has all the cosmetic items in the image collection. Test set 1 contains the cosmetic images with room background. Test set 2 is the cosmetic image which has a hand holding the cosmetic items. Last is test set 3, this test set has more illumination than test set 1 and test set 2.

We categorize the cosmetic database into 5 classes by brand of cosmetic items and each brand divided into 5 classes by type of cosmetic items, for which the size of all the cosmetic images is 512x512 pixels. Our method is performed and the efficiency is shown in Figs. 12-15.

Table 4. The details of each brand type.

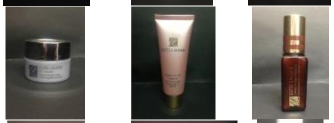
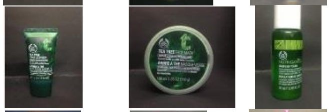
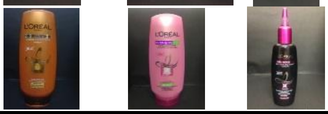
Brand Type	Brand Name	Logo	In-Brand Information	Shape & Color	Example Images
Type 1	Big	None	Small	Similar	
Type 2	Medium	Medium	Outstanding	Similar	
Type 3	Medium	Outstanding	Medium	Different	
Type 4	None	Small	Outstanding	Similar	
Type 5	Big	Big	Outstanding	Different	

Table 5. Cosmetic images collection.

Brand Type	Images
Type 1	
Type 2	
Type 3	
Type 4	
Type 5	

Table 6. Test set cosmetic images.

Test Set	Images
1	
2	
3	

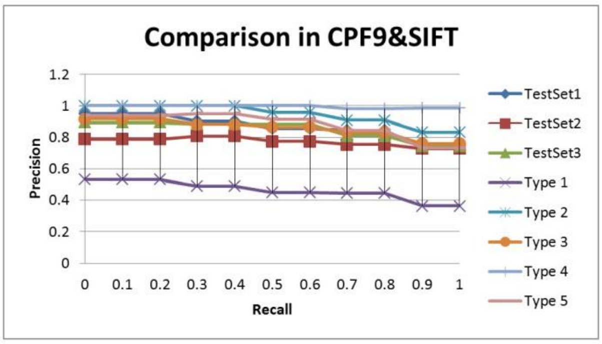


Fig. 12. Precision and recall diagram of comparison in CPF level 9 & SIFT.

Fig. 13. Precision and recall diagram of comparison in SIFT.

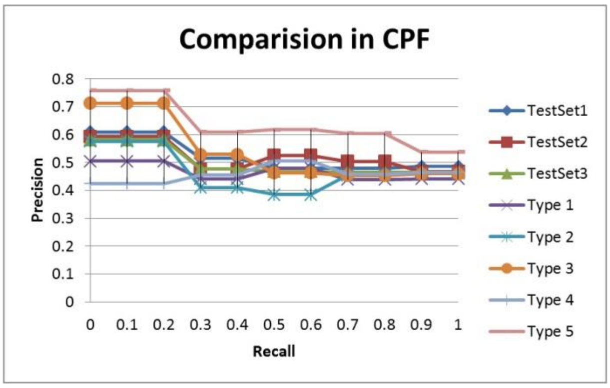


Fig. 14. Precision and recall diagram of comparison in CPF.

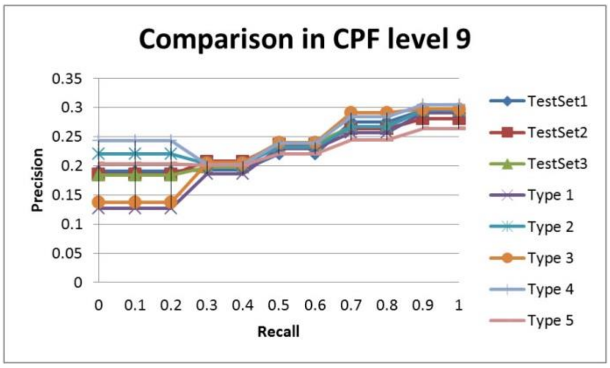


Fig. 15. Precision and recall diagram of comparison in CPF level 9.

From Figs. 12 –15, we have shown the precision and recall diagram from each methodology. Then, we can summarize and compare all the experimental result in Table 7 and Fig. 16.

The average computation time of CPF, SIFT and CPF level 9 & SIFT is shown in Table 8 and Table 9. We do not need to compare CPF and CPF level 9 to other methods because CPF uses very high computation time.

Table 7. Summarize the performance of 4 methods.

Brand Type	CPF level9 & SIFT	SIFT	CPF/ CPF level 9
1	Result: Not good Reason: The type name of this brand is small and not clear.	Result: Not good Reason: The type name of this brand is small and not clear.	Result : Not good Reason: Many cosmetic items in this brand are similar in color and shape.
2	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: Not good Reason: Many cosmetic items in this brand are similar in color and shape.
3	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: Good Reason: The color and shape in this brand can classify easily.
4	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: Not good Reason: Many cosmetic items in this brand are similar in color and shape.
5	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: High accurate Reason: The type name of this brand is clear and outstanding.	Result: High accurate Reason: The color and shape in this brand can classify easily.

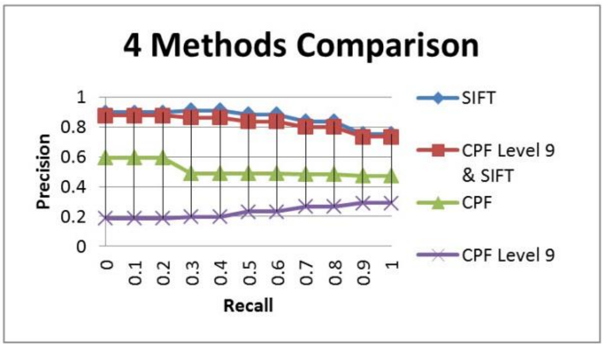


Fig. 16. Precision and recall diagram of comparison of 4 methods.

Table8. Comparing average computation time for each method.

Method	Average Computation Time (s)					Average Computation Time (s)
	Brand Type 1	Brand Type 2	Brand Type 3	Brand Type 4	Brand Type 5	
CPF level 9 & SIFT	0.114	0.112	0.089	1.896	0.218	0.489
SIFT	0.232	0.228	0.182	3.900	0.392	0.987
CPF Level 9	2102.18	2312.67	2006.25	6190.71	2214.26	2965.21
CPF	2625.71	2312.62	2398.8	7748.05	2792.12	3675.46

Table9. Comparing average computation time of CPF level 9 & SIFT to each method.

Method	Average Computation Time (s)	Method	Average Computation Time (s)	Average Time Decrease from Each Method(%)
SIFT	0.987	CPF level 9 & SIFT	0.489	50.46
CPF Level 9	2965.21	CPF level 9 & SIFT	0.489	99.98
CPF	3675.46	CPF level 9 & SIFT	0.489	99.99

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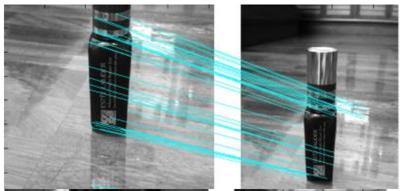
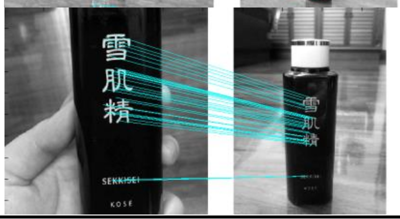
4.3. Matching Small Part Cutting of Image

We cut a square part from complete cosmetic image. Then, we test the small part of image to image collection. The experimental result is shown in Table 10.

Table10. Result of square part cosmetic images match to database.

Input Image	Complete Image	Matching Result
		
		
		

4.4. Discussion

From Fig. 10, the CPF image pyramid hierarchy of input cosmetic image (size 4096x4096) has 12 hierarchy levels. Our experiment starts from image pyramid hierarchy at level 6 (size 64x64) to level 12 (size 4096x4096). The number of matching points is increased when the number of the hierarchy level is increased. Thus, the number of matching points depends on the image size.

According to Fig. 11, CPF&SIFT at level 6, level 7 and level 8 have very low precision and recall. On the other hand, CPF&SIFT at level 9 to level 12 have very high precision and recall. However, Table 3 shows that computation time increases when the hierarchy level increases. From level 8 to level 9, the computation time increases 23.2% but from level 9 to level 10 increase up to 116.8%. Hence, we decide to use CPF image pyramid at level 9 to perform the CPF&SIFT and we call our methods as CPF level 9 & SIFT. The result is shown in Figs. 12 – 16 as precision and recall diagrams from various experiment cases.

According to Figs. 12 – 15, the diagrams compare the precision and recall of 4 methods for each brand type and 3 test sets. The result of test set 1, test set 2 and test set 3 shows no different in every method. Although test set 1 which contains the cosmetic images with room background and test set 2 which has a hand holding the cosmetic items have a lot of noises in the image, the result shows that the different in noise does not have the impact to the efficiency of our method. Even test set 3 has more illumination than test set 1 and test set 2, the result shows that the illumination change also does not make the efficiency of our method decreased. From these reasons, we can conclude that applying CPF pyramid with SIFT still keep the strong points of SIFT as well.

From mentioned above, we can summarize the result of our brand type experiment in Table 7. Our method, CPF level 9 & SIFT has the best result when using with the cosmetic item that has outstanding brand name, logo and type information. If the brand name, logo or type information is not clear and not outstanding, it is difficult to retrieve the cosmetic item correctly. Thus, the result will have lower precision and recall compare to outstanding brand name, logo and type information cosmetic item. However, from Table 8 and Table 9, if there is much information in cosmetic details, the computation time will be increased as in brand type 4. The cosmetic image with less details and information of brand name and type will give an inaccurate result or error as in brand type 1.

Then, we compare the precision and recall of 4 methods in Fig. 16, Table 8 and Table 9 which show that CPF level 9 & SIFT can reduce SIFT computation time by 50.46%. Furthermore, our method can reduce CPF computation time and CPF level 9 computation times nearly 100%.

CPF level 9 & SIFT is faster than SIFT about 50% because of the number of interest points of SIFT has been decreased by CPF. SIFT use the image size of 2^nx2^n pixels so the computational efficiency is $O(n^2)$ when n is the level of hierarchy. On the other hand, CPF level 9 & SIFT use the filtered image with the size of 2^{n-1}x2^{n-1} pixels so the computational efficiency is $O(n^2/4)$. Hence, we improve the computational efficiency from $O(n^2)$ of SIFT to $O(n^2/4)$ of CPF level 9 & SIFT.

The last experiment shows that cutting some parts of complete cosmetic image can perform the experiment correctly if the cutting part still keeps the prominent points of the image as shown in Table 10.That make we can define the size of input image by using only the smallest part with prominent points.

5. Summary and Future Work

Our method of using multi-descriptors for cosmetic image retrieval is by applying global feature and local feature together. We represent CPF as global feature and SIFT as local feature so our method is called CPF&SIFT. Moreover, CPF at level 9 gives the best result so CPF level 9 & SIFT is used in our research. This method can improve the efficiency of cosmetic image retrieval by decreasing computation time and without reducing accuracy. From the experiment, we provide CPF image pyramid hierarchy to reduce the computational efficiency in SIFT process. The result also shows that CPF level 9 & SIFT preserves efficiency measure by precision and recall from comparing to SIFT because CPF can extract the interest points of the image that still keep the main prominent features.

According to Fig. 11, the image size of cosmetic image would not smaller than 256x256 pixels because it will give the very low accurate result. However, the biggest image size should be 1024x1024 pixels because the image size that is bigger than 1024x1024 pixels does not increase accuracy much but waste a lot of computation time instead as shown in Table 3 and Fig. 11. Thus, the image size should be between 256x256 pixels and 1024x1024 pixels, to give the satisfactory results and fast processing.

Even CPF level 9 & SIFT give the accurate result, input image should be image with outstanding brand name, logo and type information. If the cosmetic image is unclear and lack of information for brand name, logo and type information, we will get the low accuracy result as in the experiment of brand type 1 case. However, the experiment of every brand types shows that CPF level 9 & SIFT gives the lower precision and recall than SIFT except brand type 4 case. That because brand type 4 has a lot of outstanding features which can be filtered by CPF very well. Hence, the precision and recall of CPF level 9 & SIFT of brand type 4 is higher than SIFT.

Although our method of cosmetic image retrieval by using multi-descriptors provides the cosmetic image retrieval with accuracy and reduced computation time, there are still some cases that give low accurate result. CPF level 9&SIFT, SIFT, CPF and CPF level 9 have different strong points and weak points for different cases which they can be supported each other. Thus, in future work, we plan to improve and develop our method to support various kinds of cosmetic images by using multi-descriptor which will give the better result for each case especially brand type 1 case. For example, combine more features such as shape and color to help improving brand type 1 case. However, brand type 1 cosmetic item is difficult to classify even by human's eyes. Last but not least, we can apply CPF level 9 & SIFT to other kinds of complex images such as Khon. Khon image retrieval can be divided into groups by using color or costume types. Khon has very strong outstanding characteristics with color. Thus, dividing the groups of Khon by color will give the best result because CPF has the potential to filter and extract the prominent points of Khon by color [24].

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