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Hybrid Method to Obtain Interest Region and Non Interest Region for Color Based Image Retrieval

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Abstract

Content based image retrieval (CBIR) has become one of the most active research areas in the past few years. Many indexing techniques are based on global feature distributions. However, these global distributions have limited discriminating power because they are unable to capture local image information. In this paper, the new proposed method based on local image to classify the Interest Region (IR) and Non Interest Region (NIR) of images. To develop this, the integration of clustering and user intervention was applied. Clustering process is obtaining several regions, meanwhile to ascertain the location of the center of images through user intervention. Several experiments are conducted using different weight (ω, γ) of IR and NIR. Subsequently average color moment is extracted from this region (IR and NIR) in CIE Lab color model. To investigate the performance, new distance is proposed based on Euclidean distance. Experimental results show the proposed method more efficient in image retrieval.

Keywords: *Interest Region, Non Interest Region, Intervention, Clustering, CBIR*

1 Introduction

In recently years, the need to access the content-based on images efficiently in various fields such as biomedicine [1-2], military [3], commerce, education, and web image classification and retrieval [4-6] have increased. Today, the biggest challenge and it is becoming important for researchers to produce effective image retrieval on a large-scale image database [7]. One of the most popular fundamental research areas is content-based image retrieval (CBIR) [8-10].

As we know in CBIR system model, content-based image retrieval searches and matches the image database of visual content based on low level features, such as color, texture or shape. However, we know that there is an obvious semantic gap between what user-queries represent based on the low-level image features and what the users think. To overcome the semantic gap, thus many researchers have investigated techniques that retain some degree of human intervention either pre-processing, during input or search thereby utilizing human semantics, knowledge, and recognition ability effectively for semantic retrieval. On the one hand, many researchers believe that the key to effective CBIR performance lies in the ability to access images at the level of objects because users generally want to search for the images containing particular object(s) of interest.

So, in this paper, we proposed a new method to classify the region, either interest region (IR) and non interest region (NIR) of images. To do this, the integration of k-means clustering method and important object are located near the center of image to decide IR and NIR. In addition, part of preprocessing technique in the proposed method that involved user intervention to reduce the semantic gap used to select the appropriate location of center on images. The remaining paper consists of: Section 2 presents the methodology of the proposed method. Section 3 describes the experimental setup. In section 4, elaborate the results and discussion and finally in section 6 contains the conclusion and feature works

2 Related Works

The object generally can be defined as a region located near the center of the image meanwhile vise verse for the non-object [12]. This leads to the central part of the available object in IR and the other parts are NIR. The conditions of useful object are located near the center of the image, significant color or texture compares its surroundings, its size relatively big and boundary pixel has a relatively strong edginess [13]. It makes sense that the center area of an image is treated more importantly than the border area of the image. Some of center regions are expected to more effectively represent the contents of the image rather than the border regions to do, because people tend to locate the most interesting object at the center of the frame when they take a picture [12]. Several regions-based retrieval methods [[13], [22-23] are proposed, because regions are correlate well with objects in an image. The authors in [13] tried to cluster regions into classes, each of which might be a group of separated regions, while in [22] represented and accessed each region separately. Likewise, especially the authors in [23] attempt to represent the content and context of regions based on color-texture classification to provide a way for semantic retrieval.

It is well known that clustering method can improved the performance of CBIR [14]. Several researchers such as [15], proposed a K-means clustering algorithm to grouping the collection of images. Image is clustered based on the query image. Color was used as features in their CBIR system. Meanwhile, in [16] proposed modified K-Means clustering to group similar pixel in CBIR. Their purpose is to improve retrieval performance by capturing the regions and also to provide a better similarity distance computation.

In order to validate the result from proposed method, the comparison with result obtained from another researcher [21] is presented. The research by [21], extract the regions using horizontal division of images into three equal non-overlapping regions. Color moment and Gabor has been extracted as features of the images. The combination of these features is used to investigate the performance.

3 Methodology

Fig. 1 depicts the general overview of the block diagram of the new proposed method in content based image retrieval (CBIR). Firstly the collection of images from a well-known database is obtained. It's follow with two parallel processes, namely image transformation and determination of central image location. One of the reasons why the CIE Lab color space was selected is that it is a perceptually uniform color space which approximates the way that humans perceive color [24]. Then, images in CIE Lab color space are cluster and convert into gray scale. Next, process followed by determining the IR and NIR of images. Finally, extract the feature by normalized color moment and provide the weight for IR and NIR. Together with the weight given for IR and NIR, the features tested against similarity measure. The detailed description of each phase is explained in the next sub-section.

3.1 K-means Clustering

In this study, we apply k-means algorithm as part methodology to analysis images similarities in the database. An algorithm is one of the most widely used of the clustering and is ease of implementation, simplicity, efficiency, and empirical success [26]. Fig. 2 represent of this algorithm [11].

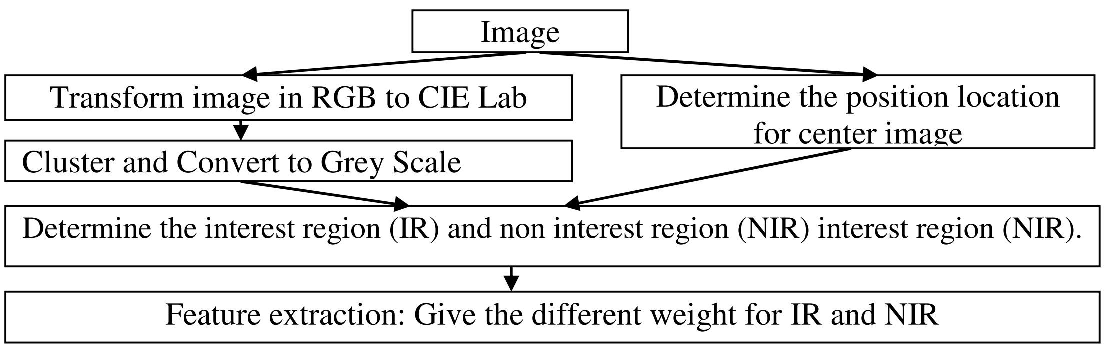


Fig. 1: Block Diagram

Purpose: The k-means algorithm for partitioning based on the mean value of the objects in the cluster.
Input: A database of N objects, number of clusters k.
Output: A set of k clusters.
Begin:

(i) Arbitrarily choose k objects as the initial cluster centers.
(ii) (Re) Assign each object to the cluster to which the object is the most similar based on the mean value of objects in the cluster.
(iii) Update the cluster means, that is, calculate the mean value of the objects for each cluster.
(iv) Repeat step (ii) and (iii) until no changes.

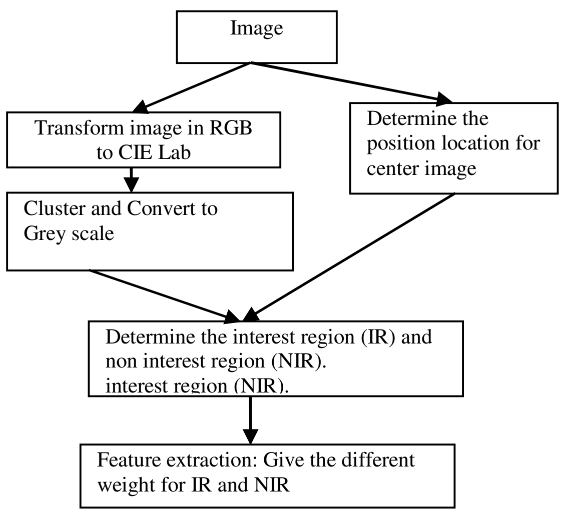
End

Fig. 2: Algorithm of k-means clustering

3.2 Determine the Location of Middle Position for an Image

The new rough technique by user observation was introduced to obtain the location of middle position of image. Fig. 3 shows an example of the different locations is selected on an image. If multiple locations in the middle position of the image are selected, it require more time for users to evaluate. Similarly, if the location of the center area is too large or small, it may not reflect the central part of the image. In this research, four different locations identified to represent the location of middle position of the images.10% of images from each category are selected randomly and marked as depicted in fig. 3. Users will evaluate the position for the central of the images based on a scale of 1.00, 0.75, 0.50 and 0.25. The value 1.0 represents the most appropriate location and followed by less appropriate, 0.25.Then intervention of user is modeled to select the most appropriate location, as a function:

$U \rightarrow \{1.00, 0.75, 0.50, 0.25\}$, which label the value of locations. The results shown that the location of the position I(a) is very high, follow by I(b), I(c) and the last is I(d). The algorithm used to calculate this is shown in Fig. 4.



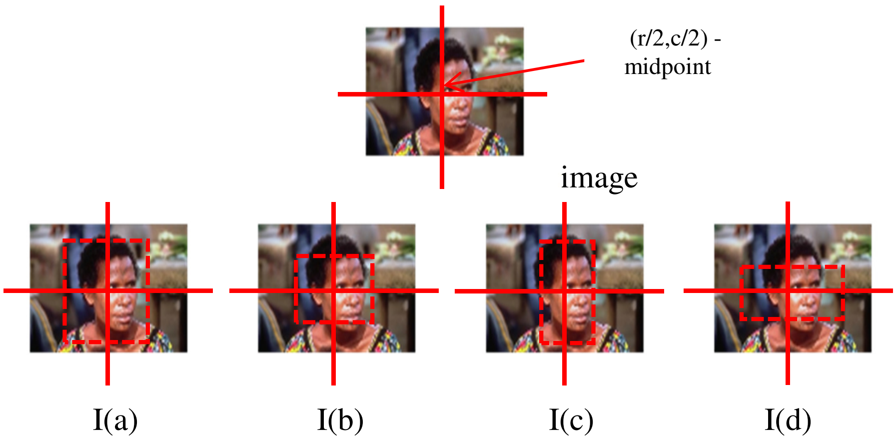


Fig. 3: Different location of middle position an image

Purpose: To determine the middle location an image
Input: Image with different location for middle an image
Output: The most suitable location for middle an image
Begin

(i) Assume the size or image, I_{rc}, where *r*=, row and *c*= column.

(ii) Calculated the midpoint (*x*,*y*) of the image (I_{rc}) using the following equation, $x = r/2$, $y = c/2$.

(iii) Extend the new *r* and new *c* from midpoint *(x,y)* to expand the area to obtain a new locations of image such as in fig. 3, with different *r* and *c*.

(iv) By users intervention, select the new locations of image as shown in fig. 3 (I(a), I(b), I(c) and I(d)) and execute the function :
$\phi : U \rightarrow \{1.00, 0.75, 0.50, 0.25\}$.

(v) Compute and find the most appropriate middle location based on step (iv).

End

Fig. 4: Algorithm to determine the most suitable location of the middle positions in the image.

Purpose: To obtain the IR and NIR
Input: Image in cluster and the best locations of middle position in the image.
Output: IR and NIR
Begin

(i) Transform clusters CIE Lab to gray scale

(ii) Assume, ϑ is the best location of the middle position in the image meanwhile C_x is the cluster, where $x = 1...n$ is number of cluster, in this case n=3.

(iii) Mapping ϑ and C_x using intersection, $\vartheta \cap C_x$. Count the pixel in the intersection based on the locations middle of image and clusters. Pixels outside of intersection will not be counted. Let β_x is the count of pixel value (not zero (0)), the resulting from $\vartheta \cap C_x$ ($\vartheta \cap C_x = \beta_x$).

(iv) Count β_x for each $\vartheta \cap C_x$.

(v) Compare the value of β_x for x =1...3, and assume, $\vartheta \cap C_1 = \beta_1$, $\vartheta \cap C_2 = C_2$ and $\vartheta \cap C_3 = \beta_3$

Suppose that $\beta_1 > \beta_2$ and $\beta_2 > \beta_3$, so C_1 is marked as IR meanwhile C_2 and C_3 are NIR.

End

Fig. 5: Algorithm to obtain IR and NIR

3.3 Feature Extraction

Color is one of the most extensively used visual content for image retrieval [17]. The authors in [18-19] provide a comprehensive survey of the various methods employed for color image indexing and retrieval in image databases. Color histograms are useful because they are relatively insensitive to position and orientation changes. It is easy to compute and is effective in characterizing both the global and local distribution of colors in an image. Considering that some of the histograms are very sparse and thus sensitive to noise, the authors in [20] proposed the cumulative color histogram. To overcome the quantization effects they subsequently presented an approach based on color moments [17]. The first three moments, mean, variance and standard deviation have shown to be efficient and effective in representing color distributions of images [17]. The following equations define the mean, variance and standard deviation of an image of size N x M.

$$\bar{x} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij}}{NM} \tag{1}$$

$$\delta^2 = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(x_{ij} - \bar{x})^2 \tag{2}$$

$$\delta = \sqrt{\frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(x_{ij} - \bar{x})^2} \tag{3}$$

where x_{ij} is the value of the pixel in row i and column j and equations (4) to (6) are used to normalize color moment.

$$\text{mean } (N\bar{x}) = [\bar{x}_\mathrm{i} - \min(\bar{x}_\mathrm{i})]. / [\max(\bar{x}_\mathrm{i}) - \min(\bar{x}_\mathrm{i})]. \tag{4}$$

$$\text{variance } (N\delta^2{}_\mathrm{i}) = [\delta^2{}_\mathrm{i} - \min(\delta^2{}_\mathrm{i})]./ [\max(\delta^2{}_\mathrm{i} - \min(\delta^2{}_\mathrm{i})]. \tag{5}$$

$$\text{std. deviation } (N\delta_\mathrm{i}) = [\delta_\mathrm{i} - \min(\delta_\mathrm{i})]./ [\max(\delta_\mathrm{i} - \min(\delta_\mathrm{i})]. \tag{6}$$

where *i,* the value color moment on a particular axis of the IR and NIR of the image. Therefore, each image will produce 18 feature vector of color moment.

3.4 Similarity measure

The method used to determine the similarity or distance of the images depends solely on the CBIR choice. The similarity tries to capture the strength of the relationship between features during comparisons of images in a database. There are many types of such methods, for example City Block distance, Manhattan distance, Euclidean distance (ED) and many others. In this study ED measure employed and this method was chosen because it is widely used in CBIR system [25]. ED is used to obtain the root of square differences for each of the extracted features between the query images with the images in the database. ED for each feature is defined as follows:

$$ED_k = \left(\sum_{k=1}^{n}(I_{n,q_k} - I_{n,i_k})^2\right)^{\frac{1}{2}} \tag{7}$$

where n =1,2,3…n, represents the number of features from the image. Meanwhile, k is the image index number in the database image. I_{n,q_k}, represents the extracted features of the query image and I_{n,i_k} represents the extracted features in the image database. The smaller value of the ED indicates that the more similar image query with the images in database and vice versa. The two images can be said to be similar if the distance, $E \approx 0$. A new distance approach based on ED is proposed to calculate the distance. The steps to compute the distance is shown below:

(i) Get regions (cluster) of each image (I) –output from 3.1. Each region, label as $c_n I_m$, where n=1,2 and 3 and m either i (image in the database) or q (image represent as a query).

(ii) Obtain the IR and NIR- output from 3.2.

(iii) Let $\overline{f_p}$, be normalized feature for each region, where p =1, 2, 3.

(iv) Give different weight of $\bar{f}_p$ for IR and NIR. The weight of IR and NIR depend on cases to investigate and relationship between weights denoted as ω and γ and represent as equation (8).

$$\omega + \gamma = 1 \tag{8}$$

Thus, the weight of the IR and NIR features shown as equations (9) and (10).

$$\text{IR} = \bar{f}_p \text{ x } \omega \tag{9}$$

$$\text{NIR} = \bar{f}_p \text{ x } \gamma \tag{10}$$

or vice versa.

(vi) Get the distance to each region of the query image (I_q) with the index image in database (I_i). I_q consisting of c_nI_q meanwhile I_i composed of c_nI_i that has been marked as IR or NIR. The distance between image regions showed as equations (11) to (13). Thus, equation (11) represents the distance between the first region, c_1I_q with c_nI_i (Δ_{11}), equation (12) for second region (Δ_{21}), c_2I_q with c_nI_i and finally equation (13) the third region (Δ_{31}), c_3I_q with c_nI_i. In this case, assume the IR is the first region c_1I_q and NIR are c_2I_q and c_3I_q.

$$\Delta_{11} = (|\, c_1I_q - c_1I_i|^{1/2},\ |\, c_1I_q - c_2I_i\,|^{1/2},\ |c_1I_q - c_3I_i\,|^{1/2})$$
$$= (|\, \bar{f}_{1q} \text{ x } \omega - \bar{f}_{1i} \text{ x } \,|^{1/2},\ |\, \bar{f}_{1q} \text{ x } \omega - \bar{f}_{2i} \text{ x } \gamma\,|^{1/2},\ |\, \bar{f}_{1q} \text{ x } \omega - \bar{f}_{3i} \text{ x } \gamma\,|^{1/2}) \tag{11}$$

$$\Delta_{21} = (\,|\, c_2I_q - c_1I_i|^{1/2},\ |\, c_2I_q - c_2I_i\,|^{1/2},\ |c_2I_q - c_3I_i\,|^{1/2}$$
$$= (|\, \bar{f}_{2q} \text{ x } \omega - \bar{f}_{1i} \text{ x } \,|^{1/2},|\, \bar{f}_{2q} \text{ x } \omega - \bar{f}_{2i} \text{ x } \gamma\,|^{1/2},\ |\, \bar{f}_{2q} \text{ x } \omega - \bar{f}_{3i} \text{ x } \gamma\,|^{1/2}) \tag{12}$$

$$\Delta_{31} = (|\, c_3I_q - c_1I_i|^{1/2},\ |\, c_3I_q - c_2I_i\,|^{1/2},\ |c_3I_q - c_3I_i\,|^{1/2})$$
$$= (|\, \bar{f}_{3q} \text{ x } \omega - \bar{f}_{1i} \text{ x } \,|^{1/2},\ |\, \bar{f}_{3q} \text{ x } \omega - \bar{f}_{2i} \text{ x } \gamma\,|^{1/2},\ |\, \bar{f}_{3q} \text{ x } \omega - \bar{f}_{3i} \text{ x } \gamma\,|^{1/2}) \tag{13}$$

Finally, the distance between the two images can be computed by the equation (14).

$$\Delta_{qI} = (\text{ minimum } (\Delta_{11}, \Delta_{12}, \Delta_{13})_a + \text{minimum } (\Delta_{21}, \Delta_{22}, \Delta_{23})_a$$
$$+ \text{ minimum } (\Delta_{31}, \Delta_{32}, \Delta_{33})_a\ )$$
$$+ (\text{ minimum } (\Delta_{11}, \Delta_{12}, \Delta_{13})_b + \text{minimum } (\Delta_{21}, \Delta_{22}, \Delta_{23})_b$$
$$+ \text{ minimum } (\Delta_{31}, \Delta_{32}, \Delta_{33})_b\ ) \tag{14}$$

where *a* and *b* axis of CIE Lab color space.

3.5 Performance: Precision and Recall

Precision and recall are used to evaluate and analyst the performance [27]. To compare the retrieval performance between different experiments, precision and recall were used. Precision (P) is defined as the ratio of the number of relevant images retrieved (N_r) to the number of total of the images retrieved K, whilst Recall (R) is defined as the number of retrieved relevant images N_r, over the total number of relevant images available in the database N_t. Precision and Recall is calculated using equation (15) and (16).

$$\text{Recall} = \frac{N_r}{N_t} \tag{15}$$

$$\text{Precision} = \frac{N_r}{K} \tag{16}$$

4 Experimental Set Up

An experiment is conducted to explore the performance of the proposed system on image download from http://wang.ist.psu/edu/. A database was created by group researcher's professor Wang from, Pennsylvania State University. This database is a subset of the Corel database and contains 1000 color images. All the images are categorized into 10 groups. Each group or category consists 100 images and size of image either 384 x 256 or 256 x 384 pixels. Table 1 lists the summary of the image in each category while fig. 7 shows an example of the images that use in the research. Ten images were randomly selected as the example images in each category. It constitutes of 100 queries. The average of 10 times retrieval precision and recall ratio is calculated as the average precision and recall for each category, and it is used to evaluate average retrieval performance. In this experiment, the relationship between parameters of weight as shown by equation (8), (9) and (10) were used to investigate the performance.

Table 1: Category of image in the database

Cat.	Number of Images	Description(semantic name)
1	100	African people and village
2	100	Beach
3	100	Building
4	100	Buses
5	100	Dinosaur
6	100	Elephants
7	100	Flowers
8	100	Horses
9	100	Mountains and glaciers
10	100	Foods

Fig. 7: Some examples of image data set

5 Results and Discussion

In order to evaluate of the proposed approach, different weight for IR and NIR has been evaluated. The weight is split in 2 cases. In case 1, the weight for IR more than NIR and the differences is maximized. Therefore, weight for IR is setting is 0.8 (a region) and NIR are 0.1 (two regions). Meanwhile, for case 2, IR less than NIR and the differences is also the maximum. The setting of weight NIR is 0.4 (two regions) and IR is 0.2. The experiment conducted base on these settings and the results are shown in Table 2a and 2b. The results show that the proposed approach using case 1 has a good performance in category 3, 5, 6, 7 and 9 meanwhile for case 2 the good performance in category 1,2,4,8 and 10. Results from table 2a and 2b are summarized in the form of a graph as shown in fig. 8. It is easy to see that given more weight of the IR demonstrated the best performance. In general, these results show that an important object located at the center of the image and should be given more attention.

Table 2a: Comparing the performance of case 1 and Case 2

Recall	Average Precision									
	Cat.1		Cat.2		Cat.3		Cat.4		Cat.5	
	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
0.0100	0.7225	0.8076	0.4320	0.4737	0.6838	0.6772	0.8222	0.8151	0.9500	0.9089
0.1000	0.2799	0.3215	0.1343	0.1703	0.3800	0.2783	0.3842	0.3983	0.8788	0.6946
0.2000	0.1994	0.2169	0.1244	0.1722	0.3095	0.2179	0.2570	0.3224	0.8096	0.6409
0.3000	0.1758	0.1877	0.1217	0.1708	0.2629	0.1959	0.1856	0.2455	0.7871	0.628
0.4000	0.1513	0.1502	0.1161	0.1616	0.2267	0.1736	0.1354	0.1725	0.7350	0.5373
0.5000	0.1342	0.1328	0.1166	0.1481	0.2066	0.1661	0.1268	0.156	0.6820	0.3694
0.6000	0.1209	0.1254	0.1128	0.1369	0.1856	0.1598	0.1057	0.1387	0.5054	0.2443
0.7000	0.1097	0.1212	0.1110	0.1311	0.1544	0.1445	0.0972	0.1241	0.0954	0.0962
0.8000	0.1036	0.116	0.1099	0.1236	0.1187	0.1295	0.0982	0.1133	0.1001	0.1005
0.9000	0.1040	0.1111	0.1080	0.112	0.1106	0.1198	0.0996	0.1078	0.1032	0.1051

1.0000	0.1039	0.1068	0.1006	0.1055	0.1074	0.1037	0.1006	0.1018	0.1043	0.1063
APR	0.2005	0.2180	0.1443	0.1733	0.2606	0.2151	0.2193	0.2451	0.5228	0.4030
% APR	20.05	21.80	14.43	17.33	26.06	21.51	21.93	24.51	52.28	40.30
% difference case 1 to case 2	-1.75	-	-3.19	-	+4.55	-	-2.58	-	+12.52	-

Table 2b: Comparing the performance of case 1 and Case 2.

Recall	**Average Precision**									
	Cat.6		**Cat.7**		**Cat.8**		**Cat.9**		**Cat.10**	
	Case 1	**Case 2**	**Case 1**	**Case 2**	**Case 1**	**Case 2**	**Case 1**	**Case 2**	**Case 1**	**Case 2**
0.0100	0.6386	0.6744	0.9127	0.7567	0.7710	0.7699	0.8743	0.7847	0.7453	0.7605
0.1000	0.3138	0.226	0.5019	0.3972	0.4008	0.2776	0.4847	0.3597	0.2990	0.3061
0.2000	0.2852	0.1820	0.3502	0.2783	0.3458	0.2605	0.5044	0.3388	0.2230	0.2465
0.3000	0.2772	0.1784	0.3078	0.2000	0.2616	0.2707	0.4711	0.344	0.2036	0.2318
0.4000	0.2230	0.1748	0.2578	0.1688	0.1944	0.2555	0.3876	0.3194	0.1763	0.2091
0.5000	0.1951	0.1621	0.2313	0.1516	0.1215	0.2383	0.3376	0.2881	0.1565	0.1904
0.6000	0.1646	0.1516	0.1561	0.1328	0.1105	0.2126	0.2865	0.2528	0.1444	0.1694
0.7000	0.1427	0.1433	0.1155	0.1224	0.1107	0.1738	0.2288	0.2194	0.1392	0.1486
0.8000	0.1208	0.1356	0.1055	0.1136	0.1093	0.1388	0.1797	0.1911	0.1274	0.1308
0.9000	0.1133	0.1240	0.1029	0.1081	0.1142	0.12	0.1260	0.1409	0.1107	0.1192
1.0000	0.1036	0.109	0.1017	0.1029	0.1079	0.1091	0.1121	0.1097	0.1021	0.1032
APR	0.2343	0.2056	0.2858	0.2302	0.2407	0.2570	0.3630	0.3044	0.2378	0.2207
% APR	23.43	20.56	28.58	23.02	24.07	25.70	36.30	30.44	22.07	23.78
% difference case 1 to case 2	+2.88	-	+5.72	-	-1.63	-	+5.85	-	-	+1.71

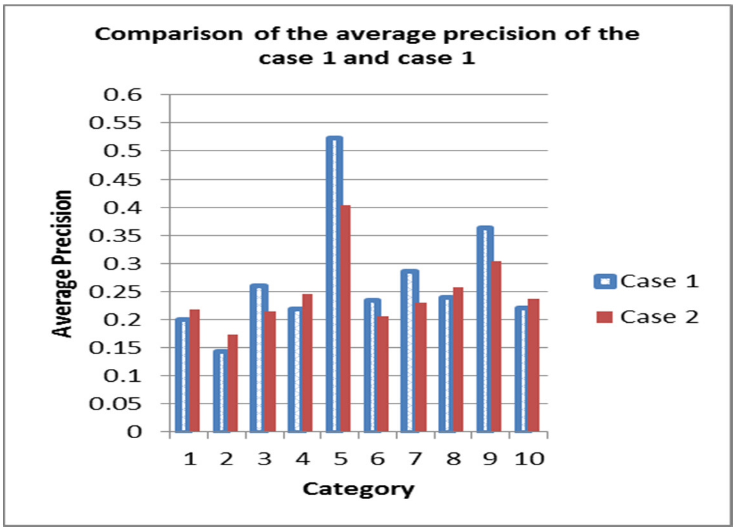


Fig. 8: Comparing the performance for case1 and case 2

In an attempt to evaluate the performance of the proposed method with another researcher, we compare the performance that proposed by [21]. The experiment was carried out based on the average of 10 query images and the result based on average precision of the retrieval of the top 10 images. Overall, the best performance is the case-1 arising from the proposed method and followed by Gabor texture features (GTF) + color moment from dividing the image into three (3) equal non overlapping horizontal regions (CMR), CMR, GTF+ color moment based on the whole image (CMW), CMW and GTF and shown as Table 3.

Table 3: Performance comparison of the proposed method with proposed in [21].

Category	Average Precision						
	Proposed by [21]					Proposed method	
	GTF	CMW	CMR	GTF + CMW	GTF + CMR	Case 1	Case 2
1	0.37	0.75	0.75	0.74	0.74	0.58	0.62
2	0.27	0.46	0.38	0.38	0.38	0.37	0.39
3	0.33	0.25	0.35	0.3	0.36	0.53	0.54
4	0.35	0.67	0.78	0.6	0.77	0.61	0.67
5	0.99	0.74	0.83	0.96	0.95	0.93	0.84
6	0.39	0.6	0.45	0.58	0.44	0.56	0.49
7	0.75	0.42	0.61	0.71	0.69	0.77	0.64
8	0.27	0.55	0.7	0.47	0.67	0.61	0.56
9	0.24	0.67	0.62	0.72	0.69	0.65	0.56
10	0.20	0.43	0.43	0.36	0.41	0.59	0.55
Average of average precision	0.416	0.554	0.59	0.582	0.61	0.62	0.586
% average	41.6	55.4	59.0	58.2	61.0	62.0	58.6

6 Conclusion and Future Work

The new method to describe the IR and NIR using the clustering and user defined location of the central region of image in image retrieval is proposed. The next process is normalized color moment in CIE Lab color space is used as a feature extraction and gives the differing weight for IR and NIR. This method also introduced the new distance based on Euclidean distance. Experimental results show that the overall performance of case 1 is better than case 2. Subsequently, the performance in case 1 is outperforms from another researcher method [21]. The future work, we apply the various area or percentage to determine the location of the center an image. Besides that, to test the optimal number of clustering, the varying methods such as Silhouette coefficient will be used. Finally, we will integrate the texture features as features.

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