THESIS FOR THE DEGREE OF MASTER

A STUDY ON CONTENT-BASED IMAGE RETRIEVAL USING REGION VECTOR

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DECEMBER, 1997

A STUDY ON CONTENT-BASED IMAGE RETRIEVAL USING REGION VECTOR

A thesis Submitted to the Faculty of
Hanyang University
By
Seok-Hwan Jang
In Partial fulfillment of the
Requirements for the Degree of
Master of Science

DECEMBER, 1997

ELECTRONIC ENGINEERING

HANYANG UNIVERSITY
GRADUATE SCHOOL

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By Seek-Hwan Jang

Entitled A STUDY ON CONTENT-BASED IMAGE RETRIEVAL USING REGION VECTOR

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Abstract

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As computer and communication systems have developed quickly, database systems using various retrieval techniques are appeared. Among these database systems, construction and retrieval techniques of several image databases have been studied in various aspects because of too much information in image databases. Since typical retrieval techniques utilize only color histogram or color coherence, their precision and recall rates appear lower than those of the proposed technique in this thesis.

We propose Region Vector that includes color and region information, so we use it to extract keyword and retrieve similar images in large image database. There are three factors in RV. The first is area, the second is 1st moment, and the third is 2nd moment.

The proposed algorithm is implemented on IBM PC with VC++ 5.0 and we report results from a database of 1,200 images and the results verify the justification and efficiency.

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1. Introduction

As information-society comes to us closely, various image databases are made. Conventional text-based retrieval systems do not retrieve images effectively because of the advent of such image databases. So to retrieve image more correctly and quickly, many techniques are studied. The techniques are divided into three categories: text-based image retrieval, content-based image retrieval, semantic-based images retrieval. Each method has its own strengths and weaknesses.

In the text-based image retrieval techniques, each image has a number of keywords describing the image itself. The retrieval technique performs keyword matching in order to retrieve relevant image. So it is easy to specify abstract query. However, it's performance only as good as text descriptions.

In the content-based image retrieval techniques, an image is analyzed based on some generic attributes such as colors, textures, and shapes. So it is suitable in large image database, for attributes of image is extracted automatically. However, this technique is hard to specify abstract queries and has less precision than the others.

In the semantic-based image retrieval techniques, semantic meanings are used to retrieve relevant images. This is more advanced technique than content-based retrieval techniques, but it is hard to implement because perfect segmentation algorithms are absent.

For large image databases, unless the images have accompanying text captions, it is often too much to expect a user to input the text descriptions manually. Besides, the manual entry of text descriptions is likely to be error-prone with incomplete or inconsistent text descriptions. In addition, some of the image databases are not confined to specific domains.

Feature generally used in content-based image retrieval is color histogram. The reason is that color histogram is simple and effective to explain natural image, has small computing time and senseless for camera viewpoint transformation. A color histogram provides no spatial information, however, it merely describes which colors are present in the image, and in what quantities. In addition, color histograms are sensitive to both compression artifacts and changes in overall image brightness. So there are many studies for advanced color histogram recently. The representative example is CCV (Color Coherence Vector) of Cornell University.

QBIC (Query by Image and Video Content) of IBM and Chabot of UC Berkeley are the most famous CBIR systems. QBIC is an image retrieval system that uses the feature as color, texture and shape information. Chabot uses relational database of images.

In this thesis, we propose image retrieval system to be familiar with user recognition, using modified color histogram embedded with spatial and shape information.

2. Related Work and Review

Recently, there has been many studies to combine both color histogram and spatial information. Hsu[13] selected first a set of representative colors from image. Then, the image was partitioned into rectangular regions, where each region was predominantly a single color. The similarity between two images was the degree of overlap between regions of the same color. He presented results from querying a database with 260 images, which showed that the integrated approach could give better results than color histograms.

Rickman and Stonham[22], randomly sampled pixel triples arranged in an equilateral triangle with a fixed side length. They used 16 levels of color hue and report results from a database of 100 images.

Smith and Chang [23] also partitioned the image into a set of regions, but their approach was more elaborate than Hsu's. They allowed a region to contain multiple different colors, and permit a given pixel to belong to several different regions.

Pass and Zabih[4] tried to make indexing using color coherence, and their proposed algorithm, CCV, completely included attributes of color histogram. In addition, it had extra feature for coherence and incoherence. We thought that CCV is the best suitable algorithm for natural image indexing among recent studies.

It also handled the images without spatial information, however, CCV recognized the same images like figure 1.

Region vector(RV) is defined to solve this problem. RV also combines shape information.

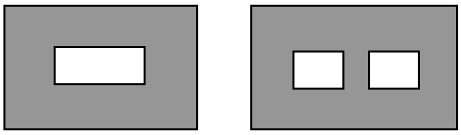


Figure 1. Sample image as same in CCV

In Hus's algorithm[13], the color histogram $H(g,i)$ of image g is obtained by counting the number of pixels with color intensity i. He assumes that H_g represents the color composition of the entire image and H_w represents the color composition of the predefined central "window."

Let CH_g denote the sorted histogram of H_g in decreasing order of the number of pixels per color. Let also CH_w denote the sorted histogram of H_w in decreasing order of the number of pixels per color. In addition, N_c denote the total number of colors to be selected. Assume we have the procedure next-non-similar-color(H,S). H is a sorted color histogram, and S is a set of colors. The procedure returns the first color in H which is not similar to any color in S.

Initialization : Background[0]←$CH_g[0]$,

Object[0]←next-non-similar-color(CH_w , Background)

Iterate to find the set of Background and Object colors.

For i = 1 to Nc/2

Background[i] = next-non-similar-color(CH_g*,Background* $\cup$ *Object)*

Object[i] = next-non-similar-color(CH_w*,Background* $\cup$ *Object)*

After color of object and background is selected, object-holding area must be determined. To perform this operation, Shannon entropy is used. We apply the maximum entropy algorithm to extract the clusters of selected colors in our images. During the first pass, the image is partitioned into four regions based on the maximum entropy discretization criterion. For each region, an evaluation criterion is used to determine whether further partitioning is needed. The expected frequency can be computed using three different methods : the uniformity assumption method, the independence assumption method, and finally the domain expert estimation.

Method 1 (Uniformity Assumption)

If no outcome is expected of occur more than the others, the probability distribution is uniform. The expected frequency of observations in a cell is estimated by

$$M \times \frac{\mu(I_{x_i})}{\mu(I_x)} \times \frac{\mu(I_{y_i})}{\mu(I_y)}$$

where M is the total number of data; I_{x_i} and I_{y_i} are the projected intervals of the cell i on X and Y respectively; and I_x and I_y are the extended intervals that enclose I_{x_i} and I_{y_i}, and μ(I_{x_i}) is the average or the expected value of I_{x_i} .

Method 2 (The Independence Assumption)

If the outcomes from I_{x_i} and I_{y_i} are independent, the expected frequency on cell i is

$$\frac{M_x(i) \times M_y(i)}{M}$$

where $M_x(i)$ and $M_y(i)$ denote the marginal frequency of the outcomes on I_{x_i} and I_{y_i} respectively.

Method 3 (Expert Estimation Assumption)

Once the expected frequencies are calculated, the deviation can be computed by

$$D = \frac{(obs(i) - \exp(i))}{\sqrt{(\exp(i))}}$$

If D exceeds a certain threshold, then the cell is covered and no further partitioning is needed. Otherwise, it is placed in a stack for subsequent passes. The partitioning process stops when either all the cells are covered or the number of samples within a cell falls below the given limit.

The similarity measurement, L, between two images g_1 and g_2 is defined as follows:

$$L_{g_1,g_2} = \sum_{k=1}^{N_c} \sum_{i=1}^{N_k^{g_1}} \sum_{j=1}^{N_k^{g_2}} C_{g_1}(i,k) \cap C_{g_2}(j,k)$$

where N_c is the total number of colors in the representative set, $N_k^{g_1}$ is the total number of clusters of color k in image g_1, $N_k^{g_2}$ is the total number of clusters of color k in image g_2, and $C_{g_1}(i,k) \cap C_{g_2}(j,k)$ is the intersection between cluster $C_{g_1}(i,k)$ and cluster $C_{g_2}(j,k)$.

In Zabih's algorithm[4], he defined a color's coherence as the degree to which pixels of that color were members of large similarly-colored regions. A pixel was coherent if the size of its connected component exceeded a fixed value τ ; otherwise, the pixel was incoherent. Let us call the number of coherent pixels of the j'th discretized color α_j and the number of incoherent pixels β_j. Clearly, the total number of pixels with j's color is $\alpha_j + \beta_j$, and so a color histogram would summarize an image as $<\alpha_j + \beta_j, ..., \alpha_n + \beta_n>$

$$\begin{matrix} 22 & 10 & 21 & 22 & 15 & 16 \\ 24 & 21 & 13 & 20 & 14 & 17 \\ 23 & 17 & 38 & 23 & 17 & 16 \\ 25 & 25 & 22 & 14 & 15 & 21 \\ 27 & 22 & 12 & 11 & 21 & 20 \\ 24 & 21 & 10 & 12 & 22 & 23 \end{matrix} \quad \longrightarrow \quad \begin{matrix} 2 & 1 & 2 & 2 & 1 & 1 \\ 2 & 2 & 1 & 2 & 1 & 1 \\ 2 & 1 & 3 & 2 & 1 & 1 \\ 2 & 2 & 2 & 1 & 1 & 2 \\ 2 & 2 & 1 & 1 & 2 & 2 \\ 2 & 2 & 1 & 1 & 2 & 2 \end{matrix}$$

Figure 2. Color discretization

Of course, the same discretized color can be associated with different labels if multiple contiguous regions of the same color exist.

B	C	B	B	A	A
B	B	C	B	A	A
B	C	D	B	A	A
B	B	B	A	A	E
B	B	A	A	E	E
B	B	A	A	E	E

Figure 3. Label result

Table 1. Label table (τ =4)

Label	A	B	C	D	E
Color	1	2	1	3	2
Size	12	15	3	1	5

Table 2. Indexing table

Color	1	2	3
α	12	20	0
β	3	0	1

Consider two images I and $I^{'}$, together with their CCV's G_I and $G_I^{'}$, and let the number of coherent pixels in color bucket j be α_j (for I) and $\alpha_j^{'}$ (for $I^{'}$). Similarly, let the number of incoherent pixels be β_j and $\beta_j^{'}$. So

$$G_I =< (\alpha_1, \beta_1), \Lambda \ \Lambda \ , (\alpha_n, \beta_n) > \qquad (1)$$

$$G_{I^{'}} =< (\alpha_1^{'}, \beta_1^{'}), \Lambda \ \Lambda \ , (\alpha_n^{'}, \beta_n^{'}) > \qquad (2)$$

Our method for comparing is based on the quantity of

$$\Delta_G = \sum \left| (\alpha_j - \alpha_j^{'}) \right| + \left| (\beta_j - \beta_j^{'}) \right| \qquad (3)$$

3. Region Vector

The proposed Region Vector(RV) is a new feature containing spatial and shape information, including the total attribute of color histogram.

RV is solution of precision depression in color histogram because it includes spatial and shape information.

3.1. Definition of RV

RV is defined about spatial and shape information to discriminate images that aren't distinguished by color histogram or CCV. Spatial information is defined as 1st moment, which is center of color coherence. Shape information is defined as 2nd moment, which means spread degree of pixels. In extracting RV, the first we discretize the true color images into 64 colors images and the scale is resized into 100*100. The second, we decompose 100*100 discretization image into 64 color-based binary images. The third, we perform the blocking process about each 64 binary images. The forth, we compute 1st and 2nd moment about object in binary images. In this process, though multi-object exists in single color, it is ignored since object of single color generally exists similar position. We compute the 2nd moment, pixel by pixel, about criterion of 1st moment. So pixel spread degree on criterion of center position is sought.

3.2 Extracting method

< step1 > Color segmentation

In true color image database, 64-color discretization is performed to achieve indexing process. To increase performance of color segmentation, blurring process is accomplished by averaging and blurred image is resized to 100*100.

< step2 > Extracting binary images

Resized image is decomposed into 64 binary images, which have single color pixels. (Figure 5)

(a) Original image

(b) Blur image by averaging

(c) 64-color discreized image

(d) 100*100 resized image and the result of step 1

Figure 4. Example for RV extraction (step 1)

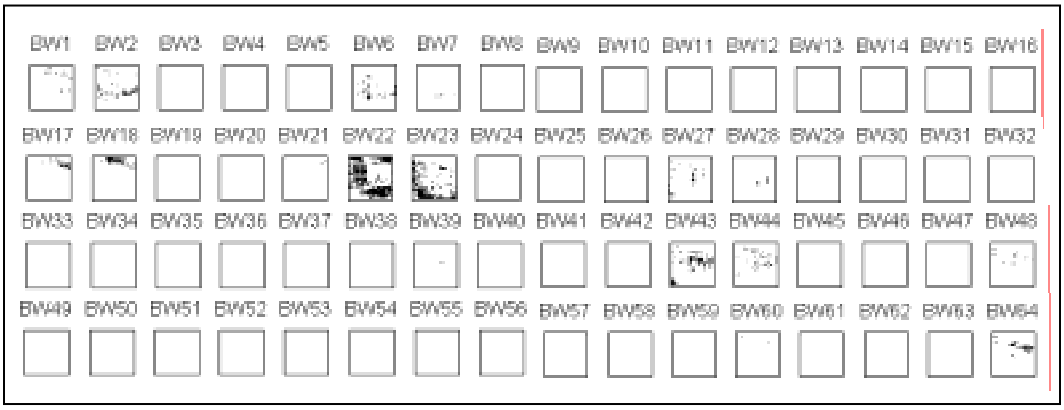


Figure 5. 64 decomposed binary images of 0005 image

< step3 >　Blocking process

Blocking process is performed for sliding 2*2 window in each 64 binary images. Blocking method is that if the value of 4 pixels in 2*2 window is 1, the window is survival, the other windows are erase. So this process erases the pixels in incoherence so that it offers low computing time in the next step, erases noise and smaller object.

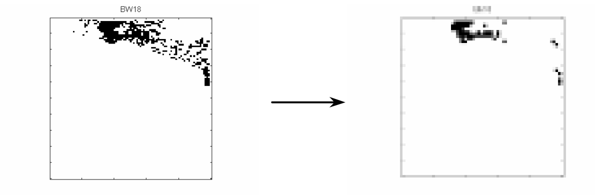


Figure 6. Example for blocking process

< step4 >　1st and 2nd moment

We compute a number of pixel, 1st and 2nd moment about each object obtained by step3. 1st moment is computed about each binary images in dividing result accumulated of x, y coordinate value by the pixel number.

Table 3. Erase pattern

$$\begin{array}{|c|c|}\hline 1 & 1 \\ \hline 0 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 1 \\ \hline 1 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 1 & 0 \\ \hline 1 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 1 & 1 \\ \hline 1 & 0 \\ \hline\end{array}$$

$$\begin{array}{|c|c|}\hline 1 & 1 \\ \hline 0 & 0 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 1 & 0 \\ \hline 0 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 1 & 0 \\ \hline 1 & 0 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 1 \\ \hline 0 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 1 \\ \hline 1 & 0 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 0 \\ \hline 1 & 1 \\ \hline\end{array}$$

$$\begin{array}{|c|c|}\hline 1 & 0 \\ \hline 0 & 0 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 1 \\ \hline 0 & 0 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 0 \\ \hline 0 & 1 \\ \hline\end{array} \quad \begin{array}{|c|c|}\hline 0 & 0 \\ \hline 1 & 0 \\ \hline\end{array}$$

2nd moment is computed by expression (4).

$$\mu_{p,q} = \sum\sum(m_{ix} - m_{ix}^{'})^{p}(m_{iy} - m_{iy}^{'})^{q} \qquad (4)$$

The extracted Region Vector is table 4 – example of 0005 image. In table 4, the

Table 4. Region Vector of 0005 image

Color	Coherence	Incoherence	Center(x)	Center(y)	Moment2.0	Moment0.2
22	1523.25	1961.88	50.05	58.23	4598.81	379.00
23	846.38	1318.50	83.24	46.11	435.62	5384.64
64	529.12	483.25	45.73	51.18	5891.06	4766.43
43	354.75	587.12	51.11	49.34	4396.66	2497.96
18	211.00	342.25	11.54	49.64	1855.81	4674.70
2	100.38	393.50	61.58	73.58	39.07	39.07
27	76.62	238.25	42.45	54.13	266.93	9.09
17	36.25	312.00	20.39	78.83	187.75	589.39
6	32.00	371.62	56.75	89.75	253.12	190.12
44	32.00	346.38	39.75	54.50	406.12	180.50
28	24.12	36.50	56.83	61.17	53.39	53.39
48	24.00	64.38	32.50	60.17	60.50	501.39
1	16.00	114.38	32.00	64.00	1352.00	800.00

second and third factors mean histogram and CCV. Total factors mean proposed RV.

3.3. Definition of similarity

In the table 4, let second item α, forth item c(x), fifth item c(y), sixth item m(x), seventh item m(y). And let s(d) similarity between images in database and query image.

$$s(d) = \sum_{i=1}^{N} \{ \; r_1 |\alpha_i - \alpha_i'| + r_2 \sqrt{(c_{ix} - c_{iy}')^2 + (c_{iy} - c_{iy}')^2}$$

$$+ r_3 \sqrt{(m_{ix} - m_{ix}')^2 + (m_{iy} - m_{iy}')^2} \; \} \qquad (5)$$

$$where, r_1 + r_2 + r_3 = 1$$

We will compare query image with database images in expression (5). To improve precision, we compute similarity between query image and null image and this similarity value is used in threshold. This is the reason that an attribute of my similarity is characterized as summation. Each factors of similarity are normalized by each method.

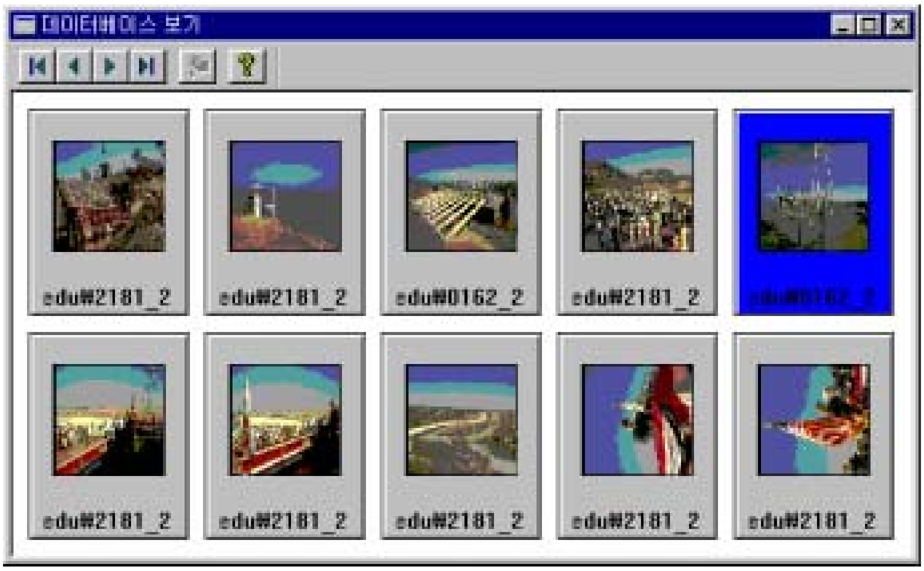
4. Experimental Results

We implement retrieval system using former extracted features and similarity. A experiment is performed in a database of some 1,200 images, which are built of Chabot, QBIC and some internet images, because standard image set like KT set, Hangul retrieval standard set, does not exist in image retrieval.

4.1 Random sample image query

(a) Query Image

(b) Retrieval Results by RV (ranking 1 ~ 10)



(c) Retrieval Results by RV (ranking 11~ 20)

Figure 7. Retrieval Result by RV

Retrieval results by RV are shown that RV is sensitive for color position and shape. When we scan color distribution of query image, it is composed by left red white flag, central black full dress, right blue sky and bottom red signs. So we know that RV is more sensitive for color position and shape.

10 images, which are the same category with query image, exist in database and they are complete retrieval in the rank of 20. Categorized database is created manually.

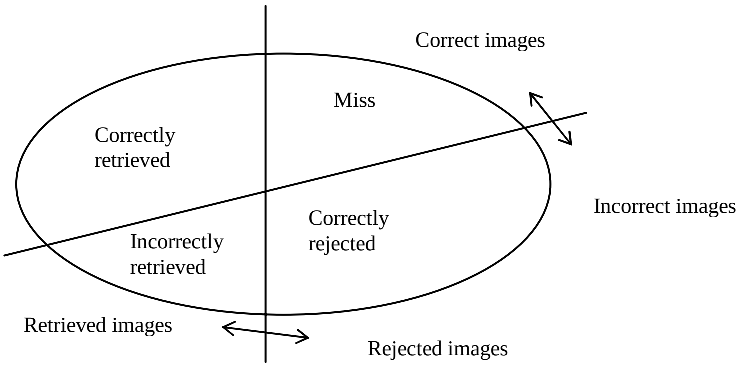


Figure 8. Partition for image group

$$precision = \frac{A}{A+B} \qquad recall = \frac{A}{A+C}$$

A : correctly retrieved images

B : incorrectly retrieved images

C : missed images

D : correctly rejected images

In the above experiment, correctly retrieved images(A) are 8, incorrectly retrieved images(B) are 2, and missed images(C) are 2. So we compute precision and recall for ranking 10 of 7-(a) query image.

precision : 0.8

recall : 0.8

In the rank of 20, correctly retrieved images are 10, incorrectly retrieved images are 10, and missed images are 10. So precision is 0.5 and recall is 1.

However, the number of retrieval images must are decided to the number of similar images in database. The number of similar images in database with 7-(a) query image are 10. So among retrieved images, only images in ranking 10 must be correctly retrieved.

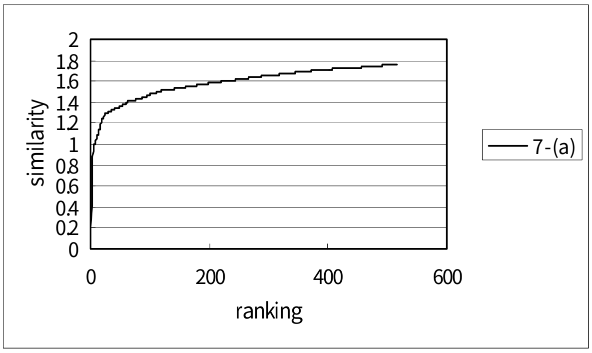
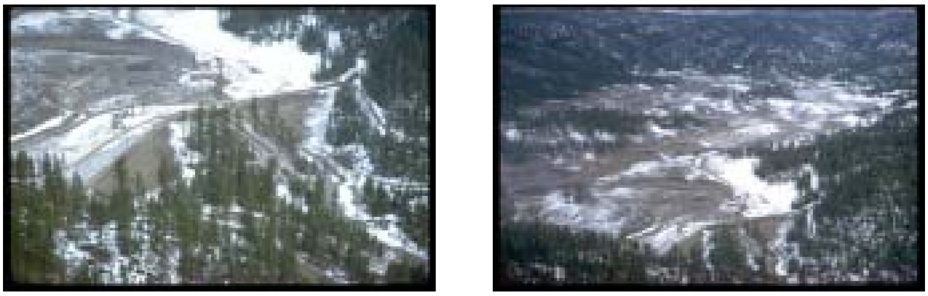


Figure 9. Retrieval ranking table of 7-(a) query image

4.2 Retrieve images by different resolution



(a) (b)

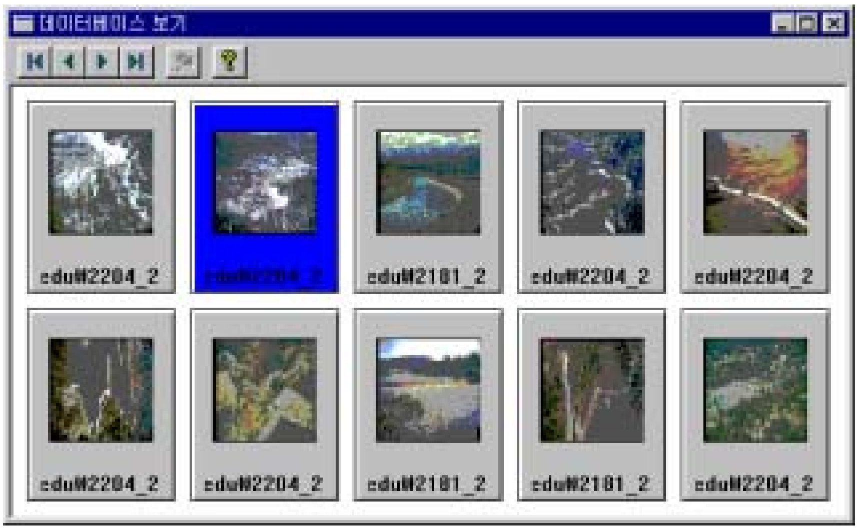
Figure 10. Similar images in different resolution

10-(a) image is to magnify the 10-(b). This two images must be retrieved into the same images.

Figure 11-(b) has images to result by retrieval of color histogram when figure 10-(a) image is query. Figure 10-(b) is not retrievd. Figure 10-(b) is retrieved in the rank of 25 by color histogram. Otherwise, in the retrieval of RV, figure 10-(b) is retrieved of the highest ranking. So RV shows powerful for different resolution. In the next time, figure 10-(b) will be query image. And color histogram and RV will be compared with each other about percesion and recall.

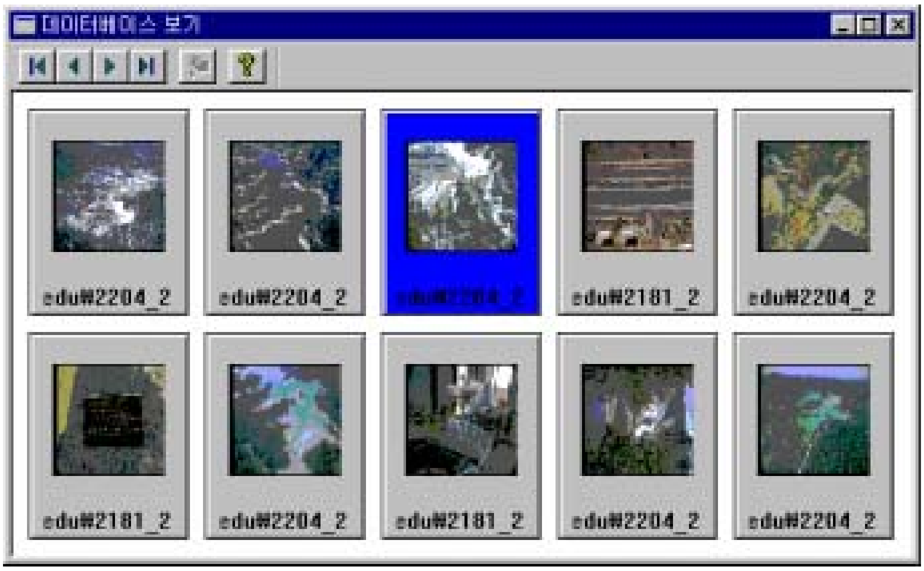
(a) Query image

(b) Retrieval results by color histogram (ranking 1~10)

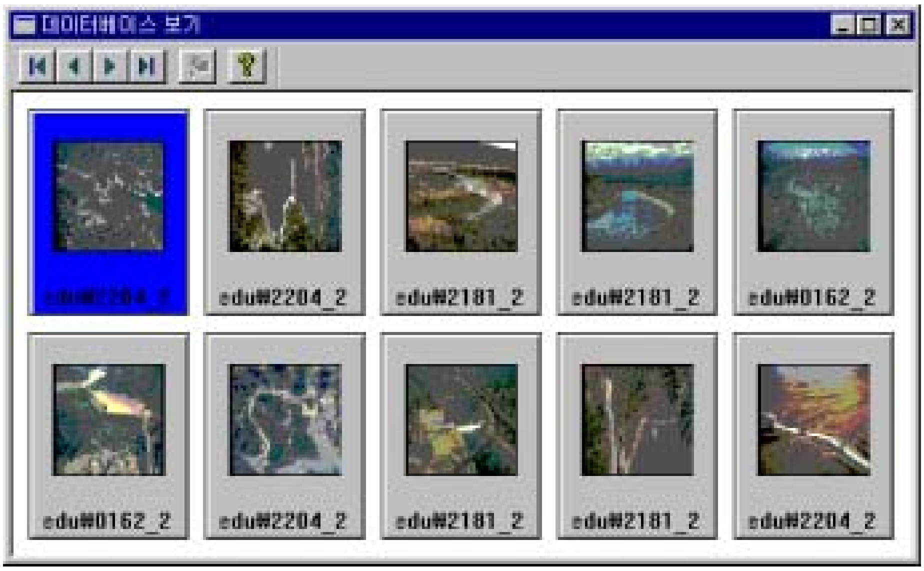


(c) Retrieval results by RV (ranking1 ~ 10)

Figure 11. Retrieval results of 10-(a) query image

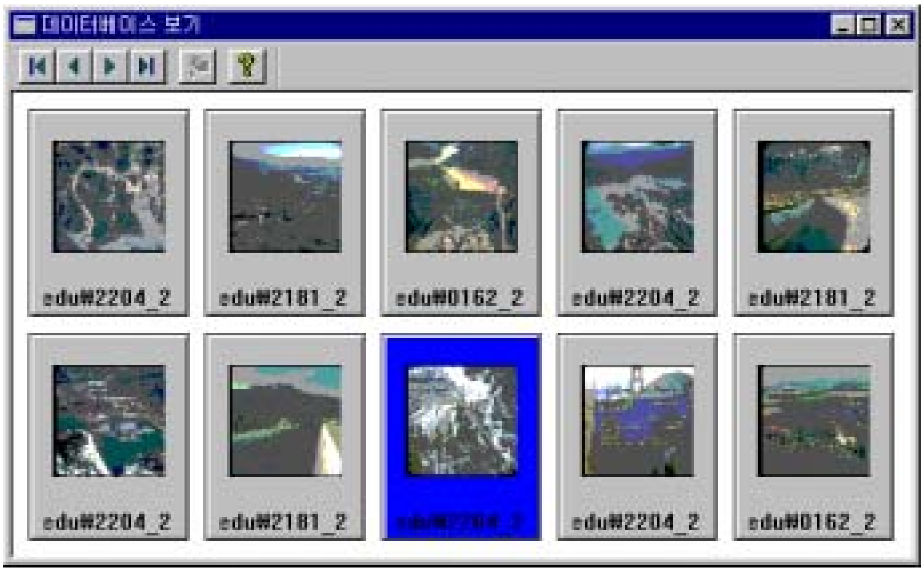


(a) Retrieval results by RV (ranking 1~10)



(b) Retrieval results by RV (ranking 10~20)

(c) Retrieval results by color histogram (ranking 1~10)



(d) Retrieval results by color histogram (ranking 11~20)

Figure 12. Retrieval results of 10-(b) query image

In these results, RV retrieves figure 10-(a) with ranking 3 for figure 10-(b) query. When the color histogram is used, 10-(a) is ranking 18.

RV retrieves figure 10-(a) for higher ranking than color histogram, but RV also does not retrieve it perfectly because just one similar image exists in database. This reason is very small database. If the database would be sufficiently large, this problem would be solved.

Figure 13 displays similarity and ranking for retrieve by 10-(a) and 10-(b). It shows that similarity distribution and retrieved image number of 10-(a) are larger than 10-(b).

When the 10-(a) is query, 261 images are retrieved and similarity distribution is values between 0 and 1. So retrieved results for 10-(a) are better than 10-(b).

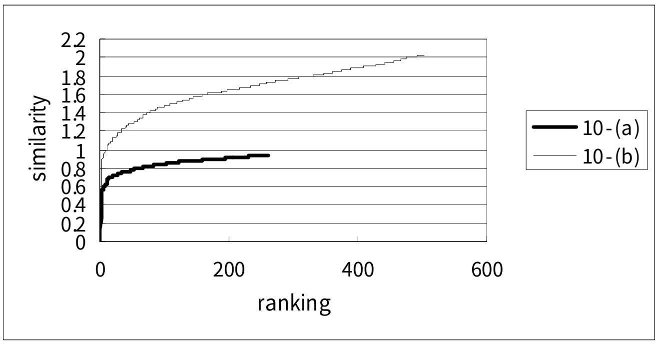


Figure 13. Query result table by figure 10-(a) and figure 10-(b)

4.3 Retrieve images by different brightness

(a) (b) (c)

(d) (e) (f)

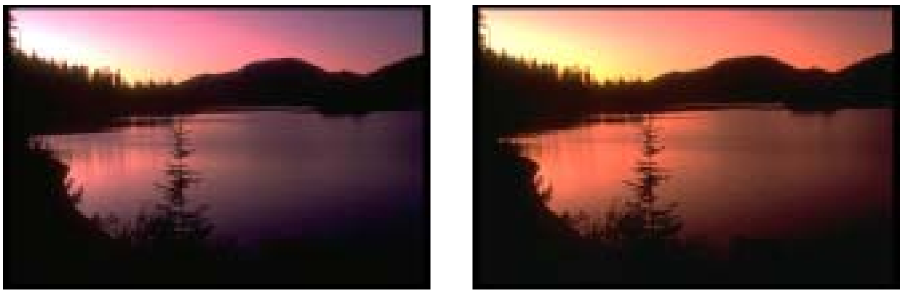
Figure 14. Similar images with different brightness

Figure 14-(a), 14-(b), and 14-(c) are similar images with different brightness and figure 14-(d), 14-(e), and 14-(f) are actual query images. Figure 14-(d) and 14-(e) have similar color distribution but different brightness. When Figure 14-(d) is given the query image, the rank of 14-(e) and 14-(f) is 32 and 36 in RV. When color histogram is used, the rank of 14-(e) and 14-(f) is 143 and 144. In such results, RV is stronger for different brightness than color histogram, but RV also impassive for different brightness.

(a) (b)

Figure 15. Similar images for different brightness

Figure 15-(a) and 15-(b) are similar images for different brightness. When the 15-(a) is query image in RV, the rank of 15-(b) is 2. When the 15-(b) is query, the rank of 15-(a) is also 2. Using color histogram, the rank of 15-(b) is also 2. However, when the 15-(b) is query, the rank of 15-(a) is 8. In this results, RV has higher ranking result than color histogram for different brightness.



(a) (b)

Figure 16. Similar images for different brightness

When the 16-(a) is query image, RV retrieves 16-(b) for ranking 2 and color histogram retrieves it for ranking 3. However color histogram retrieves figure 17 for ranking 2. This is the result that spatial information is absent.

Figure 17. Similar image with 16-(a) but rotated image

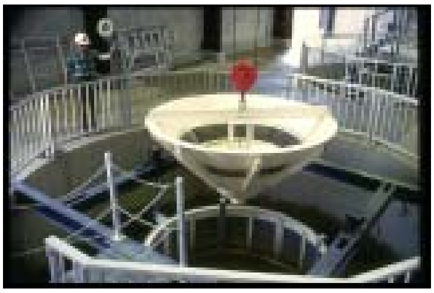
4.4 Experimental Results and Analysis

In this thesis, the result images depend on human's recognition, because proposed RV includes spatial and shape information. RV does not retrieve rotated image like as figure 17 for the highest ranking. When human shows figure 17 and figure 16-(b), 16-(b) is more similar than 17 for human. This shows RV depends on human's recognition.

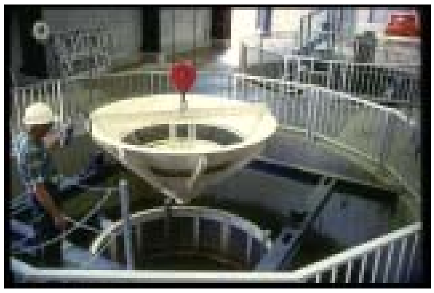
(a) (b)

Figure 18. Similar sample images as figure 15.

Using figure 16,17, and 18, precision and recall of RV are searched for ranking 10. In these similar images, A is 3, B is 7, and C is 2 when figure 16-(a) is query. So precision is 0.3 and recall is 0.6.

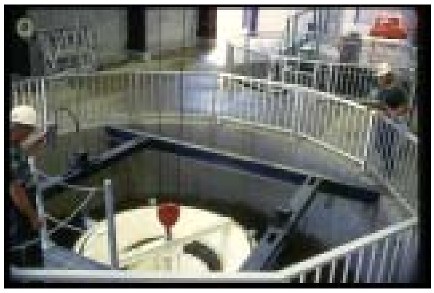


(a)

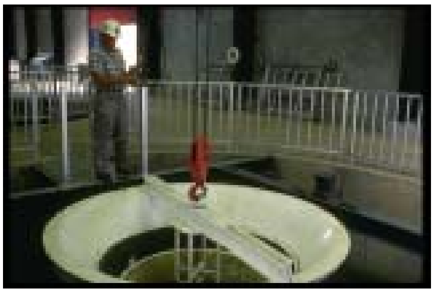


(b)

(c)



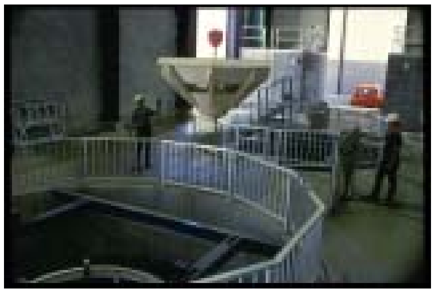
(d)



(e)

(f)

(g)



(h)

(j)

Figure 19. Similar images in database

As precision and recall is searched for using figure 19, precision is 0.4 and recall is 0.45 in the rank of 10. In the rank of 20, precision is 0.45 and recall is 0.56

(a)

(b)

(c)

(d)

(e)

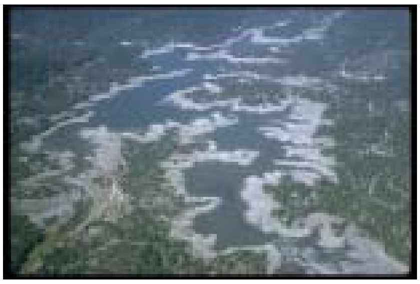
(f)

(g)

(h)

(i)

(j)



(k)

Figure 20. Similar images in database

Using proposed RV in this paper, we search precision and recall for figure 20. In the results of ranking 10, precision is 0.5 and recall is 0.46.

In the results of ranking 20, precision is 0.45 and recall is 0.82

5. Conclusion

Using proposed RV in this thesis, precision and recall appear very higher than other method about images having special color pattern like figure 7-(a). And they appear higher on images of different resolution. However, average recall is 0.5 about different brightness while precision is lower. This show that RV is senseless about different brightness, but sensitive than color histogram.

Table 5. Precision and recall for RV

Query images	Ranking 10		Ranking 20	
	precision	recall	precision	recall
7-(a)	0.8	0.8	0.5	1
16-(a)	0.3	0.6	0.2	0.8
19-(a)	0.4	0.45	0.25	0.56
20-(a)	0.5	0.46	0.45	0.82
average	0.5	0.58	0.35	0.8

In this thesis, same weight is used about target images. In the future, feedback algorithm, changing weight about attribute of images, will be studied.

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요 지

컴퓨터와 통신 시스템의 급속한 발전으로 다양한 정보검색 시스템을 이용한 데이터베이스 시스템이 등장하고 있다. 그 중에서도 이미지는 많은 정보를 내포하고 있기 때문에, 이미지데이터베이스 구축 및 검색방법이 다양하게 연구되어져 왔다.

기존의 검색 방법은 공간 정보를 배제한 칼라 성분 분포와 뭉침정도 만을 이용한 검색으로 검색의 정확도가 낮게 나타났다.

본 논문에서는 보다 정확한 이미지 데이터베이스검색을 위하여 칼라와 공간정보를 포함한 Region Vector 를 정의하고 이를 이용한 키워드 추출 알고리즘 및 대용량 이미지 데이터베이스상의 유사이미지 검색 방법을 제안한다.

제안된 Region Vector 는 영역, 1 차 모멘트 및 2 차 모멘트로 구성되는데, 색 분포, 색 뭉침 뿐만 아니라 퍼짐 정도를 포함하여 대상 이미지에 대한 특징으로 사용한다.

제안한 방법은 IBM PC 상에서 Visual C++ 5.0 을 사용하여 구현하였으며, 1,200 여 개의 이미지를 대상으로 실험을 수행하였고 기존방법보다 정확도가 향상됨을 보임으로써 Region Vector 를 이용한 이미지 검색 방법의 효율성을 검증한다.