Content Based Image Retrieval Using Color, Texture and Shape Features

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CONTENT BASED IMAGE RETRIEVAL USING DOMINANT COLOR, TEXTURE AND SHAPE

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Abstract :

In these days people are interested in using digital images. So the size of the image database is increasing enormously. Lot of interest is paid to find images in the database. There is a great need for developing an efficient technique for finding the images. In order to find an image, image has to be represented with certain features. Color, texture and shape are three important visual features of an image. In this paper we propose an efficient image retrieval technique which uses dynamic dominant color, texture and shape features of an image. An image is uniformly divided into 8 coarse partitions as a first step. After the above coarse partition, the centroid of each partition ("color Bin" in MPEG-7) is selected as its dominant color. Texture of an image is obtained by using Gray Level Co-occurrence Matrix (GLCM). Color and texture features are normalized. Shape information is captured in terms of edge images computed using Gradient Vector Flow fields. Invariant moments are then used to record the shape features. The combination of the color and texture features of an image in conjunction with the shape features provide a robust feature set for image retrieval.Weighted Euclidean distance of color, texture and shape features is used in retrieving the similar images. The efficiency of the method is demonstrated with the results.

Keywords: Image retrieval, dominant color, Gray level co-occurrence matrix, Gradient vector flow field.

1. Introduction

Content-based image retrieval (CBIR) [1] has become a prominent research topic because of the proliferation of video and image data in digital form. Increased bandwidth availability to access the internet in the near future will allow the users to search for and browse through video and image databases located at remote sites. Therefore fast retrieval of images from large databases is an important problem that needs to be addressed.

Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. CBIR is an important alternative and complement to traditional text-based image searching and can greatly enhance the accuracy of the information being returned. It aims to develop an efficient visual-Content-based technique to search, browse and retrieve relevant images from large-scale digital image collections. Most proposed CBIR [2,3,4] techniques automatically extract low-level features (e.g. color, texture, shapes and layout of objects) to measure the similarities among images by comparing the feature differences.

Color, texture and shape features have been used for describing image content. Color is one of the most widely used low-level visual features and is invariant to image size and orientation [1]. As conventional color features used in CBIR, there are color histogram, color correlogram, and dominant color descriptor (DCD).

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Color histogram is the most commonly used color representation, but it does not include any spatial information. Color correlogram describes the probability of finding color pairs at a fixed pixel distance and provides spatial information. Therefore color correlogram yields better retrieval accuracy in comparison to color histogram. Color autocorrelogram is a subset of color correlogram, which captures the spatial correlation between identical colors only. Since it provides significant computational benefits over color correlogram, it is more suitable for image retrieval. DCD is MPEG-7 color descriptors [4]. DCD describes the salient color distributions in an image or a region of interest, and provides an effective, compact, and intuitive representation of colors presented in an image. However, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution [5, 6]. In [7], Yang et al. presented a color quantization method for dominant color extraction, called the linear block algorithm (LBA), and it has been shown that LBA is efficient in color quantization and computation. For the purpose of effectively retrieving more similar images from the digital image databases (DBs), Lu et al. [8] uses the color distributions, the mean value and the standard deviation, to represent the global characteristics of the image, and the image bitmap is used to represent the local characteristics of the image for increasing the accuracy of the retrieval system.

In [3,12] HSV color and GLCM texture are used as feature descriptors of an image. Here HSV color space is quantized with non-equal intervals. H is quantized into 8-bins, S into 3-bins and v into 3-bins. So color is represented with one dimensional vector of size 72 (8X3X3). Instead of using 72 color Feature values to represent color of an image, it is better to use compact representation of the feature vector. For simplicity and with out loss of generality the RGB color space is used in this paper.

Texture is also an important visual feature that refers to innate surface properties of an object and their relationship to the surrounding environment. Many objects in an image can be distinguished solely by their textures without any other information. There is no universal definition of texture. Texture may consist of some basic primitives, and may also describe the structural arrangement of a region and the relationship of the surrounding regions [5]. In our approach we have used the texture features using gray-level co-occurrence matrix (GLCM).

Shape feature has been extensively used for retrieval systems [22, 23]. Image retrieval based on visually significant points [24, 25] is reported in literature. In [26], local color and texture features are computed on a window of regular geometrical shape surrounding the corner points. General purpose corner detectors [27] are also used for this purpose. In [28], fuzzy features are used to capture the shape information. Shape signatures are computed from blurred images and global invariant moments are computed as shape features.

The objective of this paper is to develop a technique which captures color and texture descriptors of an image, and has a shape descriptor in terms of invariant moments computed on the edge image. Gradient Vector Flow (GVF) fields [29] are used to compute the edge image, which will capture the object shape information. GVF fields give excellent results in determining the object boundaries irrespective of the concavities involved. Invariant moments are used to serve as shape features.

Our proposed CBIR system is based on Dominant color [21] and GLCM [17] texture and shape [29]. But there is a focus on global features. Because Low level visual features of the images such as color, texture and shape are especially useful to represent and to compare images automatically. In the concrete selection of color, texture and shape description, we use dominant colors, Gray-level co-occurrence matrix and Gradient vector flow field. The rest of the paper is organized as follows. The section 2 outlines proposed method. The section 3 deals with experimental setup. The section 4 presents results. The section 5 presents conclusions.

2. Proposed Method

Only simple features of image information can not get comprehensive description of image content. We consider the dominant color, texture and shape features combining not only be able to express more image information, but also to describe image from the different aspects for more detailed information in order to obtain better search results. The proposed method is based on dominant color, texture and shape features of image.

Retrieval Algorithm :

Step1: Uniformly divide each image in the database and the target image into 8-coarse partitions as shown in Fig.1.
Step2: For each partition, the centroid of each partition is selected as its dominant color.
Step3: Obtain texture features (Energy, Contrast, Entropy and inverse difference) from GLCM.
Step4: Obtain invariant moments of Gradient Vector Flow Fields as shape features
Step5: construct a combined feature vector for color, texture and shape.

Step6: Find the distances between feature vector of query image and the feature vectors of target images using weighted and normalized Euclidean distance.
Step7: Sort the Euclidean distances.
Step8: Retrieve first 20 most similar images with minimum distance.

2.1. Color Feature Representation

In general, color is one of the most dominant and distinguishable low-level visual features in describing image. Many CBIR systems employ color to retrieve images, such as QBIC system and Visual SEEK. In theory, it will lead to minimum error by extracting color feature for retrieval using real color image directly, but the problem is that the computation cost and storage required will expand rapidly. So it goes against practical application. In fact, for a given color image, the number of actual colors only occupies a small proportion of the total number of colors in the whole color space, and further observation shows that some dominant colors cover a majority of pixels. Consequently, it won't influence the understanding of image content though reducing the quality of image if we use these dominant colors to represent image.

In the MPEG-7 Final Committee Draft, several color descriptors have been approved including number of histogram descriptors and a dominant color descriptor (DCD) [4, 6]. DCD contains two main components: representative colors and the percentage of each color. DCD can provide an effective, compact, and intuitive salient color representation, and describe the color distribution in an image or a region of interesting. But, for the DCD in MPEG-7, the representative colors depend on the color distribution, and the greater part of representative colors will be located in the higher color distribution range with smaller color distance. It is may be not consistent with human perception because human eyes cannot exactly distinguish the colors with close distance. Moreover, DCD similarity matching does not fit human perception very well, and it will cause incorrect ranks for images with similar color distribution. We will adopt a new and efficient dominant color extraction scheme to address the above problems [7, 8].

According to numerous experiments, the selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, the RGB color space is used. Firstly the image is uniformly divided into 8 coarse partitions, as shown in Fig. 2. If there are several colors located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition is selected as its quantized color. Let X=(XR, XG,XB) represent color components of a pixel with color components Red, Green, and Blue, and Ci be the quantized color for partition i.

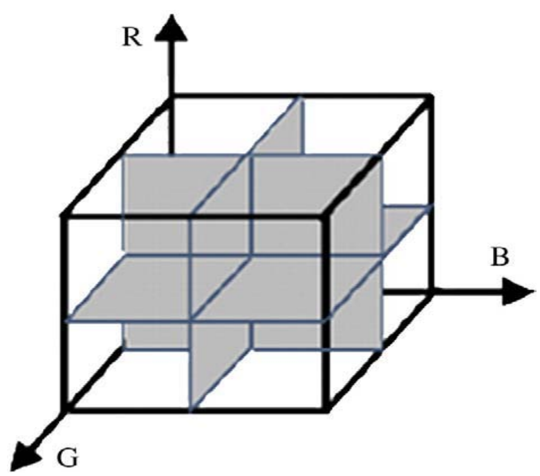


Fig. 1. The coarse division of RGB color space.

2.2. Extraction of dominant color of an image

The procedure to extract dominant color of an image is as follows:

According to numerous experiments, the selection of color space is not a critical issue for DCD extraction. Therefore, for simplicity and without loss of generality, the RGB color space is used. Firstly, the RGB color space is uniformly divided into 8 coarse partitions, as shown in Fig. 2. If there are several colors located on the same partitioned block, they are assumed to be similar. After the above coarse partition, the centroid of each partition ("color Bin" in MPEG-7) is selected as its quantized color.

Let X=(XR, XG,XB) represent color components of a pixel with color components Red, Green, and Blue, and Ci be the quantized color for partition i.

The average value of color distribution for each partition center can be calculated by

$$\overline{X_i} = \frac{\sum_{x \in C_i} X}{\sum_{x \in C_i} 1}$$

After the average values are obtained, each quantized color can be determined by using

$$C_i = (\overline{X}_i^R, \overline{X}_i^G, \overline{X}_i^{\mathbf{B}})(1 \le i \le 8)$$

In this way, the dominant colors of an image will be obtained.

2.3. Extraction of texture of an image

Most natural surfaces exhibit texture, which is an important low level visual feature. Texture recognition will therefore be a natural part of many computer vision systems. In this paper, we propose a texture representation for image retrieval based on GLCM. List may be presented with each item marked by bullets and numbers.

GLCM [11, 13] is created in four directions with the distance between pixels as one. Texture features are extracted from the statistics of this matrix. Four GLCM texture features are commonly used which are given below:

GLCM is composed of the probability value, it is defined by P(i,j|d,θ) which expresses the probability of the couple pixels at θ direction and *d* interval. When θ and *d* is determined, P(i,j|d,θ) is showed by $P_{i,j}$. Distinctly GLCM is a symmetry matrix and its level is determined by the image gray-level. Elements in the matrix are computed by the equation shown below:

$$P(i,j|d,\theta) = \frac{P(i,j|d,\theta)}{\sum_i \sum_j P(i,j|d,\theta)} \qquad (4)$$

GLCM expresses the texture feature according the correlation of the couple pixels gray-level value at different positions. It quantificationally describes the texture feature. In this paper, four texture features are considered. They include energy, contrast, entropy, inverse difference.

$$Energy E = \sum_x \sum_y P(x,y)^2 \qquad (5)$$

It is texture measures of gray-scale image represent homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$Contrast I = \sum \sum (x-y)^2 P(x,y) \qquad (6)$$

Contrast is the main diagonal near the moment of inertia, which measures how the values of the matrix are distributed and number of images of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture.

$$\text{Entropy } S = -\sum_x \sum_y P(x,y) \log P(x,y) \qquad (7)$$

Entropy measures randomness in the image texture. Entropy is minimum when the co-occurrence matrix for all values is equal. On the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

$$\text{Inverse Difference } H = \sum_x \sum_y \frac{1}{1+(x-y)^2} P(x,y) \qquad (8)$$

It measures number of local changes in image texture. Its value in large is illustrated that image texture between the different regions of the lack of change and partial very evenly. Here $p(x, y)$ is the gray-level value at the Coordinate (x, y).

The texture features are computed for an image when d=1 and ϑ***=0^0^, 45^0^, 90^0^, 135^0^***. In each direction four texture features are calculated. They are used as texture feature descriptor. Combined feature vector of Color and texture is formulated.

2.4 Extraction of Shape of an image

Shape information is captured in terms of the edge image of the gray scale equivalent of every image in the database. We have used gradient vector flow (GVF) fields to obtain the edge image [29].

Gradient Vector Flow:

Snakes, or active contours, are used extensively in computer vision and image processing applications, particularly to locate object boundaries. Problems associated with their poor convergence to boundary concavities, however, have limited their utility. Gradient vector flow (GVF) is a static external force used in active contour method. GVF is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the images. It differs fundamentally from traditional snake external forces in that it cannot be written as the negative gradient of a potential function, and the corresponding snake is formulated directly from a force balance condition rather than a variational formulation.

The GVF uses a force balance condition given by

$$F_{\text{int}} + F_{ext}^{(p)} = 0$$

Where F_{int} is the internal force and $F_{ext}^{(p)}$ is the external force. The external force field $V(x, y)$ is referred to as the GVF field. The GVF field $V(x, y)$ is a vector field given by $V(x, y) = [u(x, y), v(x, y)]$ that minimizes the energy function

$$\varepsilon = \int\int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |v - \nabla f|^2 dxdy$$

This variational formulation follows a standard principle that of making the results smooth when there is no data. In particular, when $|\nabla f|$ is small, the energy is dominated by the sum of squares of the partial derivatives of the vector field, yielding a slowly varying field. On the other hand, when $|\nabla f|$ is large, the second term dominates the integrand, and is minimized by setting $V = |\nabla f|$. This produces the desired effect of keeping nearly equal to the gradient of the edge map when it is large, but forcing the field to be slowly-varying in homogeneous regions. The parameter μ is a regularization parameter governing the trade-off between the first term and the second term in the integrand.

The GVF field gives excellent results on concavities supporting the edge pixels with opposite pair of forces, obeying force balance condition, in one of the four directions (horizontal, vertical and diagonal) unlike the traditional external forces which support either in the horizontal or vertical directions only. The algorithm for edge image computation is given below:

Algorithm: (edge image computation)

1. Read the image and convert it to gray scale.
2. Blur the image using a Gaussian filter.
3. Compute the gradient map of the blurred image.
4. Compute GVF. (100 iterations and $\mu = 0.2$)
5. Filter out only strong edge responses using $k\sigma$, where σ is the standard deviation of the GVF. (k Value used is 2.5).
6. Converge onto edge pixels satisfying the force balance condition yielding edge image

3. Experimental Setup

3.1 Data set: Wang's [15] dataset comprising of 1000 Corel images with ground truth. The image set comprises 100 images in each of 10 categories. The images are of the size 256 x 384 or 384X256. But the images with 384X256 are resized to 256X384.

3.2 Feature set: The feature set comprises color texture and shape descriptors computed for an image as we discussed in section 2.

Color: For every image eight dominant colors are extracted by coarse partitioning the R, G and B planes into equal halves.

Texture: In each of 0^0, $45^{0,}$ 90^0 and 135^0 four statistical features i.e. energy, entropy, inverse difference and homogeneity combining a total of 16 statistical features are calculated from GLCM.

Shape: Translation, rotation, and scale invariant one-dimensional normalized contour sequence moments are computed on the edge image [24, 25]. The gray level edge images of the R, G and B individual planes are taken and the shape descriptors are computed as follows:

$$F_1 = \frac{(\mu_2)^{1/2}}{m_1}$$

$$F_2 = \frac{\mu_3}{(\mu_2)^{3/2}}$$

$$F_3 = \frac{\mu_4}{(\mu_2)^2}$$

$$F_4 = \overline{\mu_5}$$

Where

$$m_r = \frac{1}{N}\sum_{i=1}^{N}[Z(i)]^r$$

$$\mu_r = \frac{1}{N}\sum_{i=1}^{N}[Z(i) - m_1]^r$$

$$\overline{\mu_r} = \frac{\mu_r}{(\mu_2)^{1/2}}$$

The Z(i) is the set of Euclidean distances between centroid and all boundary pixels of the digitized shape.

A total of 12 features result from the above computations. In addition, moment invariant to translation, rotation and scale is taken on R, G and B planes individually considering all the pixels [24]. The transformations are summarized as below:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\gamma}}$$

Where

$$\gamma = \frac{p+q}{2} + 1 \text{ (Central moments)}$$

$$\phi = \eta_{20} + \eta_{02} \text{ (Moment Invariant)}$$

The above computations will yield additional 3 features amounting to a total of 15 features.

The distance between two images is computed as D = D1+ D2 + D3, where D1 and D2 are the distance computed by integrated matching scheme at two resolutions and D3 is the distance resulting from shape comparison.

3.3 Computation of similarity

The similarity between query and target image is measured from two types of characteristic features which includes dominant color and texture features. Two types of characteristics of images represent different aspects of property. So during the Euclidean similarity measure, when necessary the appropriate weights to combine them are also considered.

Therefore, in carrying out Euclidean similarity measure we should consider necessary appropriate weights to combine them. We construct the Euclidean calculation model as follows:

$$D(A,B) = \omega_1 D(F_{CA}, F_{CB}) + \omega_2 D(F_{TA}, F_{TB}) + \omega_3 (F_{SA}, F_{SB})$$

Here ω_1 is the weight of color features, ω_2 is the weight of texture features, F_{CA} and F_{CB} represents the 8 three dimensional color features for image A and B. For a method based on GLCM, F_{TA} and F_{TB} on behalf of 16 texture features correspond to image A and B. F_{SA} and F_{SB} represents 15 invariant color moments of GVF as shape features. Here, we combine color texture and shape features. The value of ω through experiments shows that at the time ω_1=0.4, ω_2=0.3 and ω_3=0.3 has better retrieval performance.

4. Experimental Results

The experiments were carried out as explained in sections 2 and 3. The results are benchmarked with some of the existing systems using the same database [15]. The quantitative measure is given below

$$p(i) = \frac{1}{100} \sum_{1 \le j \le 1000,\, r(i,j) \le 100,\, ID(j)=ID(i)} 1$$

Where *p(i)* is precision of query image I, ID(i) and ID(j) are category ID of image I and j respectively, which are in the range of 1 to 10. the r(i, j) is the rank of image j. This value is percentile of images belonging to the category of image i , in the first 100 retrieved images.

The average precision p_t for category **t(**1≤t≤10) is given by

$$p_t = \frac{1}{100} \sum_{1 \le i \le 1000,\, ID(i)=t} p(i)$$

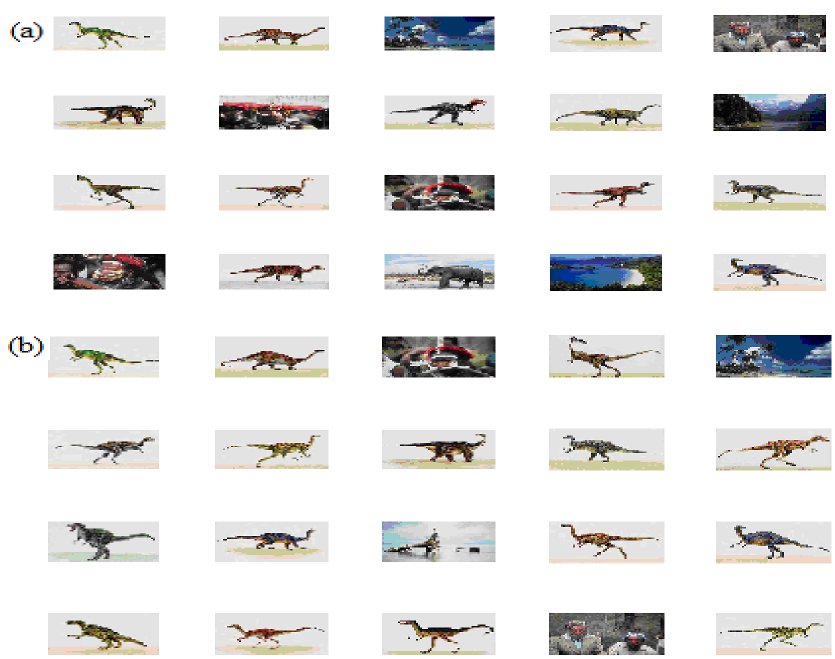
The comparison of proposed method with other retrieval systems is presented in the Table 1. These retrieval systems are based on HSV color, GLCM texture and combined HSV color and GLCM texture. Our sub-blocks based retrieval system is better than these systems in all categories of the database.

The experiments were carried out on a Core i3, 2.4 GHz processor with 4GB RAM using MATLAB. Fig. 2 shows the image retrieval results using Dominant color, Dominant Color and GLCM texture[30] and the proposed method. The image at the top left- hand corner is the query image and the other 19 images are the retrieval results.

The performance of a retrieval system can be measured in terms of its recall (or sensitivity) and precision (or specificity)**.** Recall measures the ability of the system to retrieve all models that are relevant, while precision measures the ability of the system to retrieve only models that are relevant. They are defined as

$$\mathrm{Re}\,call = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images}}$$

$$precision = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of images retrieved}}$$



(c)

Fig. 2 The image retrieval results(dinosaurs) using different techniques (a) retrieval based on Dominant color (b) retrieval based on Dominant color and GLCM texture[30] (c) retrieval based on proposed method

Table1. Comparison of average precision obtained by proposed method with other retrieval techniques.

Class	Average Precision		
	Dominant color	Dominant color+GLCM Texture	Dominant color +GLCM Texture+Shape
Africa	0.21	0.27	0.42
Beaches	0.35	0.36	0.39
Building	0.5	0.25	0.43
Bus	0.22	0.52	0.65
Dinosaur	0.29	0.91	0.97
Elephant	0.24	0.38	0.63
Flower	0.73	0.89	0.9
Horses	0.25	0.47	0.65
Mountain	0.18	0.3	0.46
Food	0.29	0.32	0.52
Average	0.326	0.467	0.602

The following graph showing the Comparison of average precision obtained by proposed method with other retrieval systems.

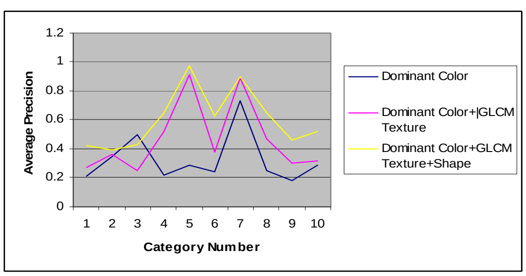


Fig. 3 Average precision of various image retrieval methods for 10 classes of corel database .

The following graph showing the Comparison of average precision obtained by proposed method with other retrieval systems.

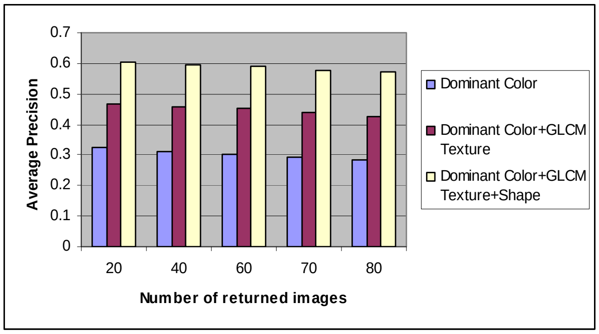


Fig. 4 Average precision of various image retrieval methods.

The following graph showing the Comparison of average recall obtained by proposed method with other retrieval systems.

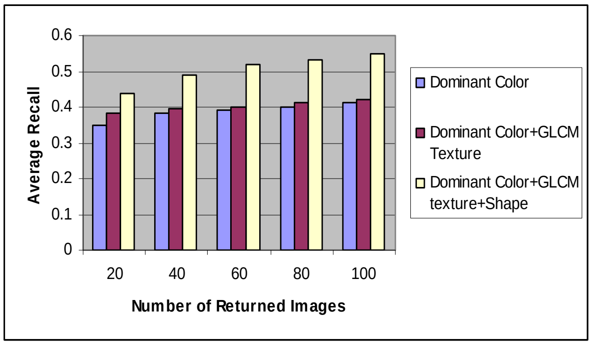


Fig. 5 Average recall of various image retrieval methods.

5. Conclusion

In this paper, a CBIR method has been proposed which uses the combination of dominant color, GLCM texture and Gradient Vector flow field representation of shape. A total of 39 features covering color, texture and shape proved that the proposed method yielded higher average precision and average recall. In addition, the proposed method almost always showed performance gain of average retrieval time over the other methods. As further studies, the proposed retrieval method is to be evaluated for more various databases.

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