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Evaluation of Unsupervised Content-Based Image Retrieval Systems by the Combination of Different Image Features

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Abstract

The process of locating pertinent images in the image database is known as an image retrieval system. Text-based and content-based image retrieval are the two main categories of image retrieval methods. The visual characteristics of a picture, such as color, texture, shape, and spatial design, are used in the content-based technique of image retrieval. On the other hand, the images are represented and indexed in a content-based manner. An approach for cluster-based graph partitioning is utilized to obtain the pictures in an unsupervised manner. In this work, many picture properties are fused to compare the performance of different CBIR systems. The performance is assessed with varying degrees of accuracy. A few current CBIR systems with the same meaning are used to compare the accuracy. It is discovered that the accuracy of the CBIR above systems is superior to that of the current systems. A standard database of 1000 identically resolved photos from COREL is used to evaluate the approaches.

Keywords: Unsupervised Content-Based Image Retrieval, Visual Features of an Image, Graph Partitioning Method

1. Introduction

Any advancement that essentially aids in the establishment of digital image databases based on their visual content is known as content-based image retrieval or CBIR. According to this argument, everything that shifts from an image-likeness task to a system that explains healthy images falls under the purview of CBIR interpretation. Observe individuals from various backgrounds, including information retrieval, information theory, computer vision, human-computer interaction, machine learning, Web and data mining, database systems, and statistics, supporting and collaborating with the CBIR organization, as they demonstrate strength in solving the ultimate problem of understanding healthy images [5, 8 and 17]. Color, texture, and shape are the three visual elements that are most frequently utilized. Specifics of each are provided as (1) Color: Since it does not depend on the orientation or dimensions of the image, one of the most popular methods is to perceive the pictures based on the colors they cover. Texture: A measure of how different textures appear in images and how they are primarily characterized. Depending on how many textures are found in the picture, texels—which represent the textures—are arranged into many groups. (3) Shape: Shape provides information about the state of a specific location that is being searched for but not about the state of an image. Shapes will frequently be resolved first by applying edge detection or segmentation to an image. Three primary tasks are carried out by a CBIR system to extract images: (a) image segmentation, (b) feature extraction, and (c) computation of similarity measures [9 and 21]. Image segmentation is the process of dividing an image into regions so that, in the end, each segment may be identified as belonging to a particular characteristic, as stated in [18]. Numerous reviews aim to consolidate different segmentation processes. The following categories can be used to classify segmentation techniques: Histogram thresholding, feature space clustering, region-based methods, edge detection techniques, graph-theoretical techniques, fuzzy techniques, and neural network techniques [11, 16, 26]. The rest of the paper is arranged as follows: For a CBIR

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method to be valuable in reality, various issues should be dealt with. Hence, the image retrieval methods, counting different basic parts of their plan, are elaborated in Section 2. Some important methods and approaches to the implementation are discussed in Section 3. The implementation of the recommended CBIR system and corresponding results are presented in Section 4. The work is concluded in Section 5.

2. Real-world CBIR systems

The real-world CBIR structures that are now in use can be divided into two groups: region-based image recovery structures and full-image recovery systems. Features are removed from the entire image without segmenting it into sections in full-image recovery structures. The entire composition of images is used in full-image recovery structures. The requested image is not administered at this time in this system because the photos in the database are segmented. The image is divided into areas prior to feature extraction in region-based structures. By then, each area's features have been eliminated. Here, the query image and the image stored in the database both make use of neighborhood features.

Furthermore, region-based structures fall into one of three categories: In the basic kind, the query image is not segmented in any way; instead, the database's images are split up, and the system searches for photos that contain the requested image in part. This process is known as sub-image recovery. In the second type, just a tiny portion of the query picture is used for searching at this stage, and the request and the database images are divided. In the third type, all of the request image's regions will be used for the connection, and both the query image and database images are divided [19 and 20].

Since locale-based frameworks are more advantageous than full-picture recuperation frameworks, a significant percentage of the existing CBIR frameworks are area-based frameworks. Locale-based frameworks divide images into smaller sections using unique division techniques. A portion of the current frameworks is (i) Blobworld, which has been created by UC Berkeley Computer Vision Group [1]. It sections the picture into blobs (areas) utilizing an (Expectation-Maximization) calculation dependent on the shading and surface highlights of the pixels. (ii) The Earth Mover's Distance, Multi-Dimensional Scaling, and Color-Based Image Retrieval, in this recovery framework, pictures are regarded as focuses in a measurement space in which they are moved generally in order to find picture neighborhoods of interest in view of shading data. This separation work is known as the Earth Mover's Distance (EMD) [13]. The framework additionally utilizes multi-dimensional scaling (MDS) strategies to embed a gathering of pictures that focuses on a few-dimensional Euclidean space so their separations are saved as much as attainable. It is a full-picture-based recovery framework [14]. (iii) PicSOM is created by the Laboratory of Computer and Information Science, Helsinki University of Technology. The picture is isolated into five districts. Shape and texture properties are utilized for every area. Also, edge and shape properties are utilized as features. Highlights are put away in a tree course of action that utilizes a self-organizing map (SOM) [10]. (iv) Simplicity (Semantics-sensitive Integrated Matching for Picture LIbraries) was created by J. Z. Wang et al. at Stanford University [22]. It portions the picture into 4 x 4-pixel squares and concentrates an element vector for each square. Utilize the k-mean grouping method to deal with a portion of the picture divided into districts. (v) UFM (Unified Feature Matching) created by Chen and Wang in 2002 [2]. UFM conspire portrays the closeness between pictures by consolidating properties of all areas in the pictures. The likeness of two pictures is then characterized as the general similitude between two groups of fluffy highlights and evaluated by a comparable measure, the UFM measure, which joins properties of the apparent multitude of areas in the pictures. It is a region-based picture recovery framework. (vi) CLUE (CLUster retrieval of pictures) was created by Chen et al. in 2006 [4]. It is known as the bunch-based recovery of pictures by unsupervised learning (CLUE), which improves client relations with picture recovery frameworks by building up closeness data. Sign recovers picture groups by applying a chart hypothetical bunching calculation to an assortment of pictures in the encompassing region of the query. Specifically, groups rely upon which pictures are recovered in reply to the query [3].

Three CBIR systems have been created in this work by combining an image's two visual characteristics. The visual contents are combined in the form of color and shape, color and texture, and shape and texture. Evaluation is done on the accuracy at various precision levels. Subsequently, the outcomes are compared with two extant CBIR systems with identical semantics, identified as UFM and CLUE.

3. Methods of research and implementations

In this paper, A CBIR strategy is built up that joins the three visual features color, shape, and textures together. It depends on the joining of visual traits and an unsupervised learning strategy. For any color model, the color instant can be determined. There are 3 color instants are calculated per channel, in the case of RGB nine instants are possible and 12 instants are possible in the case of CMYK [6and 24].

The source color instant can be taken as the typical color in the image, and it might be controlled by the following mean (Mi) balance:

$$M_i = \sum_{j=1}^{j=N} \frac{Probij}{N} \qquad (1)$$

Here, *N* decides the total amount of possible pixels in the image and Prob*ij*indicates the value ith color channel and jth pixel of the image.

The Standard deviation (SD) is the second color instant. It is done by calculating the square root of the variance of the distribution of color.

$$SD = \sqrt{(\frac{1}{N}\sum_{j=1}^{j=N} 1 * |Mi - Probij|^2} \quad (2)$$

Here, $M_i$is the mean of the image ith color channel

The *skewness* (Skewi) is the third color instant. It evaluates how unstable color spreading is, and in this way, it provides facts regarding the color spreading outline. It can be computed by the following relation:

$$Skewi = \sqrt[\frac{2}{3}]{\sqrt{(\frac{1}{N}\sum_{j=1}^{j=N}(Probij - Mi)^3)}} \quad (3)$$

Shape traits are measured using Gradient Vector Flow (GVF) fields. In this, the images are partitioned into segments. GVF is frequently used in image processing for examining the number of chunks in the image. By this, it retrieves the shape trait of an image. It is presented by Xu and Prince, reported in [23].

The GVF is given by Vector [(x, y) = [a(x, y), b[x, y)] that shrinks the functional of energy:

$$S(GVF) = \iint_{R^2} |\Delta f|^2 \, |Vector - \nabla f|^2 + \mu(ax^2 + ay^2 + bx^2 + by^2)dxdy \quad (4)$$

Here, f is a two-dimensional image function f(x, y) known as an edge map characterized on the image range.

Texture features (T) are evaluated by statistical Tamura feature and multi-resolution filtering methods. Multi-resolution filtering methods comprise Gabor and Wavelet transform depicts texture by the statistical scattering of the image intensity [7]. The texture measure is given by the following equation [12]:

$$T(i,j) = \frac{1}{W^2}\sum_{m=-w}^{m=w}\sum_{n=-w}^{n=w} Edge(i+m, j+n) \quad (5)$$

Here, *w = 2w + 1*, it shows observation window size.

The CBIR system fuses the values of color, shape, and texture traits by using the above equations. Then these trait values are stored in the feature database. A restriction of 0.7 (says a threshold value of 70%) is allotted for the texture, color and shape features values. The mathematical model of the recommended CBIR system is given by the following relations.

$$(Color - Shape) = Skewi + S(GVF) \quad (6)$$

$$(Color - Texture) = Skewi + T(i,j) \quad (7)$$

$$(Shape - Texture) = S(GVF) + T(i,j) \quad (8)$$

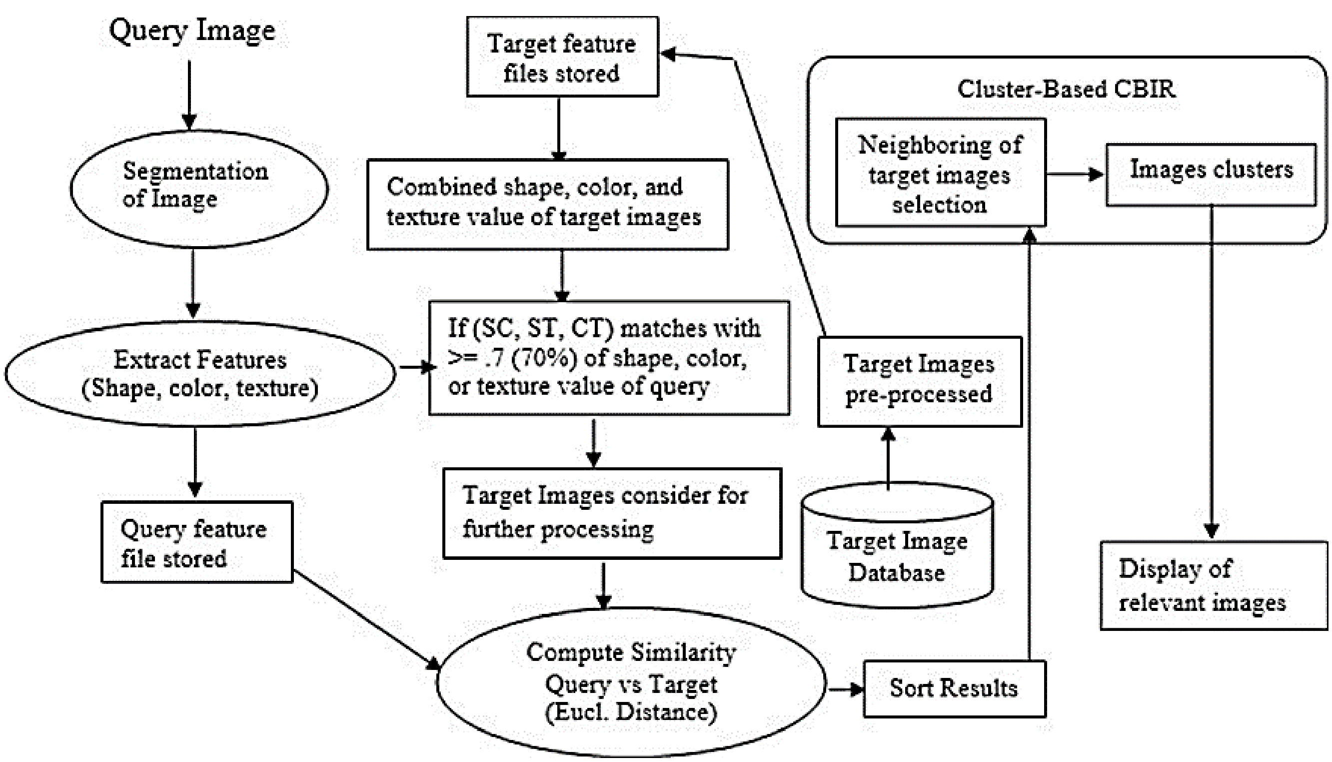

Figure 1. The CBIR System based on a fusion of visual traits

The same restriction also fixed for the query image as 70% of the color, shape, and texture traits values of the query image. If the color, shape, and texture visual traits values of a target image are above the threshold value for the color, shape, and texture visual traits respectively, the color, shape, and texture traits values of the target images are combined and save in the stored features database. If not, discard the target image as a significant image The structure of the CBIR system which based on a combination of visual traits is shown in Figure 1.

This approach combines the values of color, shape, and texture traits of each image and put away that feature values in the database of features. At that point look at the color, shape, and texture features estimations of the target image with joined of two visual contents color & shape, color & texture, shape & texture traits values of each image. If the feature values of color and shape, color and texture, and the shape and texture of a target image are larger than the 70% value for the color, shape, and texture visual contents values respectively, add up the color & shape, color & texture, and shape & texture values of the object images and save them in the stored features database. If not, the images are discarded as the relevant image [15, 25].

4. Results and Discussions

The exploratory outcomes have been performed with a generally helpful COREL image database, which contained 10 distinct classes of pictures, each class has 100 pictures of dimension 256 X 384, and absolute around contained 1,000 pictures appeared in Table 1. The Euclidean distance as the similarity measure is used for evaluating the similarity between the query and target images in the database.

$$Distance(x, y) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (9)$$

Precision reflects all extracted images into account. Precision is evaluated at a given cut off rank 0.7.

$$Precision = \frac{|Relevant\ Images\ upto\ k|}{|Total\ Images\ Retrieved\ upto\ k|} \quad (10)$$

$$P\ (atk = 100) = \frac{|P_1 + P_2 + \ldots + P_{100}|}{|k = 100|} \quad (11)$$

Once a query image is received, the system displays a list of computed similarity measure values for the distinct images in the database. After that, it shows a list of images in a decreasing manner of their similarity with the query image. Presently, just the main 25 outputs are shown because of space restriction, for the one arbitrarily selected query image with distinct semantics from each model of combination of two visual traits, from the flower category shown in Figure 2 (a – c).

Table 1: Description of Image Database with Index Values: COREL [27]

Class No.	Class Name	Class No.	Class Name	Class No.	Class Name
1 (0-99)	People and village	5 (400-499)	Dinosaurs	9 (800-899)	Mountains and glaciers
2 (100-199)	Beach	6 (500-599)	Elephants	10 (900-999)	Food
3 (200-299)	Buildings	7 (600-699)	Flowers		
4 (300-399)	Buses	8 (700-799)	Horses		

Figure 2(a). The CBIR technique produces a blend of features related to color and shape: Of the top 25, there are 21 images that are similar.

CBIR system Results for flower category with same query image: The first image is the query image, and at the top of each image is given image ID (Class number) and similarity measure. The consequences of CBIR approaches are broken down by those likewise dependent on unsupervised learning. The top k results have been chosen from the CBIR methods to calculate precision,i.e., precision at k. The average precision values have been taken at varying precision levels of k of each CBIR model and reported in corresponding tables: Table 2, Table 3, and Table 4, respectively. The performance of five CBIR systems at an average precision of 100 for each class of image database is reported in Table 5. The five CBIR systems are UFM, CLUE, Color-Shape, Shape-Texture, and Color-Texture. It was experimentally found that the CBIR models combined with two visual features produce better results than the other existing methods. The performance of these CBIR systems is pictorially shown in Figure 3 and Figure 4, respectively. Overall, it is also observed that the CBIR model, in terms of color and texture, outperforms.

Figure 2(b). *Combinations of shape and texture features are produced using the CBIR system: Out of the top 25, there are twenty images that are comparable.*

Figure 2(c). *Combinations of color and texture features are produced by the CBIR system: Of the top 25, there are 23 images that are similar.*

Table 2: Performance of the CBIR system using a threshold of 0.7 and a mixture of color and shape characteristics at different precision levels of k for each class of image database

ID	Name	10	20	30	40	50	60	70	80	90	100
1	People	0.72	0.675	0.667	0.636	0.615	0.595	0.59	0.585	0.58	0.57
2	Beach	0.68	0.655	0.617	0.586	0.554	0.535	0.505	0.475	0.446	0.42
3	Buildings	0.61	0.555	0.537	0.506	0.485	0.454	0.433	0.415	0.395	0.39
4	Buses	0.81	0.785	0.767	0.746	0.725	0.71	0.705	0.697	0.688	0.68
5	Dinosaurs	1.00	0.996	0.987	0.980	0.978	0.975	0.973	0.972	0.971	0.97
6	Elephants	0.59	0.534	0.487	0.436	0.395	0.386	0.38	0.375	0.369	0.36
7	Flowers	0.86	0.856	0.847	0.838	0.829	0.825	0.82	0.818	0.815	0.81
8	Horses	0.86	0.854	0.845	0.842	0.841	0.84	0.839	0.838	0.836	0.83
9	Mountains	0.54	0.535	0.517	0.492	0.475	0.442	0.415	0.398	0.387	0.37
10	Food	0.77	0.755	0.742	0.727	0.713	0.702	0.7	0.697	0.695	0.69
Avg	All Categories	0.744	0.72	0.701	0.678	0.661	0.646	0.636	0.627	0.618	0.609

Table 3: Performance of the CBIR system using a threshold of 0.7 and a mixture of shape and texture characteristics at different precision levels of k for each type of image database

ID	Category Name	10	20	30	40	50	60	70	80	90	100
1	People	0.73	0.693	0.671	0.653	0.642	0.632	0.615	0.593	0.586	0.581
2	Beach	0.70	0.649	0.621	0.616	0.601	0.595	0.577	0.563	0.496	0.452
3	Buildings	0.64	0.572	0.559	0.536	0.523	0.511	0.486	0.471	0.423	0.413
4	Buses	0.83	0.779	0.771	0.763	0.753	0.742	0.737	0.727	0.713	0.712
5	Dinosaurs	1.00	0.996	0.992	0.987	0.981	0.976	0.975	0.974	0.973	0.971
6	Elephants	0.59	0.546	0.491	0.474	0.442	0.428	0.412	0.408	0.396	0.372
7	Flowers	0.88	0.858	0.853	0.842	0.831	0.828	0.823	0.820	0.817	0.813
8	Horses	0.87	0.858	0.851	0.853	0.848	0.844	0.841	0.840	0.838	0.832
9	Mountains	0.57	0.531	0.527	0.517	0.502	0.476	0.463	0.427	0.415	0.39
10	Food	0.80	0.769	0.761	0.732	0.723	0.712	0.709	0.701	0.699	0.69
Avg	All Categories	0.761	0.725	0.709	0.697	0.684	0.674	0.664	0.652	0.635	0.623

Table 4: Performance of the CBIR system using a threshold of 0.7 and a mixture of color and texture features at different precision levels of k for each type of image database

ID	Category Name	10	20	30	40	50	60	70	80	90	100
1	People	0.70	0.685	0.676	0.646	0.625	0.615	0.598	0.587	0.582	0.57
2	Beach	0.68	0.645	0.628	0.605	0.575	0.555	0.525	0.485	0.476	0.46
3	Buildings	0.64	0.595	0.567	0.546	0.525	0.494	0.483	0.475	0.462	0.45
4	Buses	0.88	0.845	0.817	0.786	0.775	0.768	0.755	0.734	0.721	0.71
5	Dinosaurs	1.00	0.995	0.979	0.977	0.974	0.973	0.973	0.972	0.971	0.97
6	Elephants	0.58	0.565	0.556	0.526	0.495	0.487	0.477	0.454	0.444	0.43
7	Flowers	0.86	0.86	0.858	0.854	0.85	0.849	0.847	0.844	0.843	0.84
8	Horses	0.90	0.894	0.89	0.888	0.88	0.879	0.874	0.873	0.872	0.87
9	Mountains	0.55	0.53	0.513	0.505	0.492	0.471	0.465	0.454	0.442	0.43
10	Food	0.78	0.77	0.769	0.767	0.761	0.754	0.75	0.749	0.742	0.74
Avg	All Categories	0.757	0.738	0.725	0.71	0.695	0.684	0.674	0.662	0.655	0.647

Table 5: Five CBIR systems performance, with an average precision of 100, for every category of image database

ID	Category Name	UFM [3]	CLUE [6]	Color-Shape [CS]	Shape-Texture [ST]	Color-Texture [CT]
1	People	0.38	0.49	0.57	0.581	0.57
2	Beach	0.31	0.34	0.42	0.452	0.46
3	Buildings	0.34	0.35	0.39	0.413	0.45
4	Buses	0.61	0.63	0.68	0.712	0.71
5	Dinosaurs	0.92	0.96	0.97	0.971	0.97
6	Elephants	0.24	0.28	0.36	0.372	0.43
7	Flowers	0.66	0.75	0.81	0.813	0.84
8	Horses	0.63	0.70	0.83	0.832	0.87
9	Mountains	0.27	0.28	0.37	0.39	0.43
10	Food	0.48	0.60	0.69	0.69	0.74
Avg	All Categories	0.484	0.538	0.609	0.623	0.647

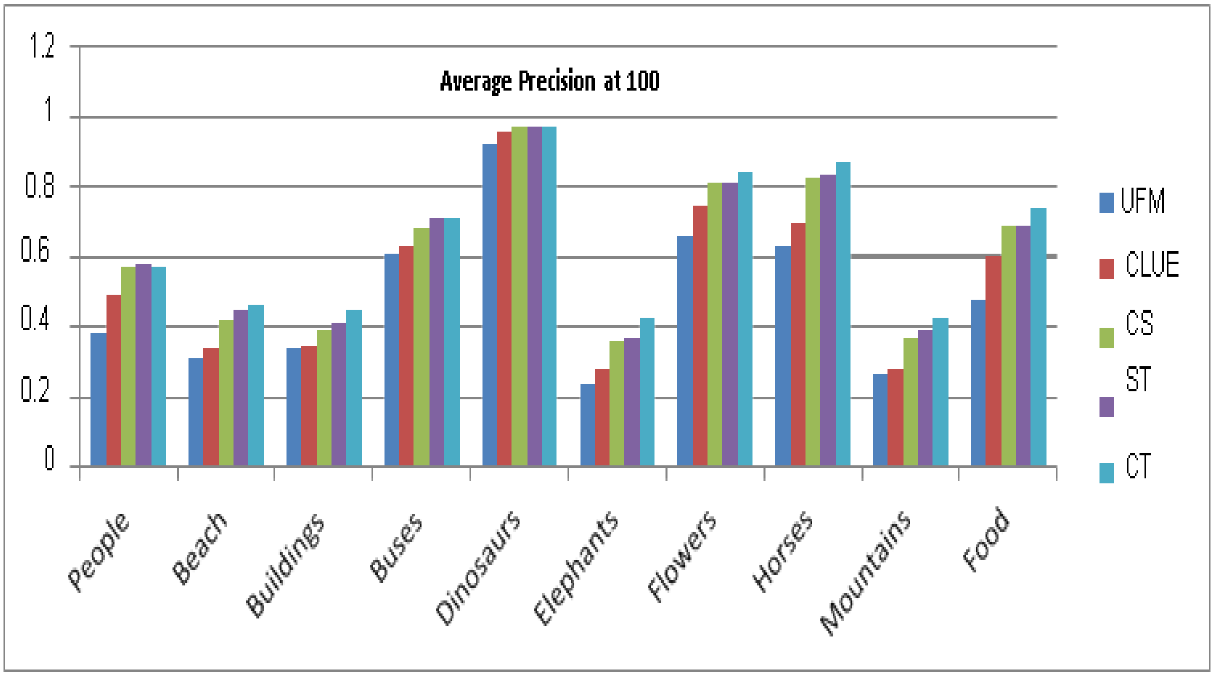

Figure 3. A comparison graph showing the average precision of five CBIR systems for each kind of image database.

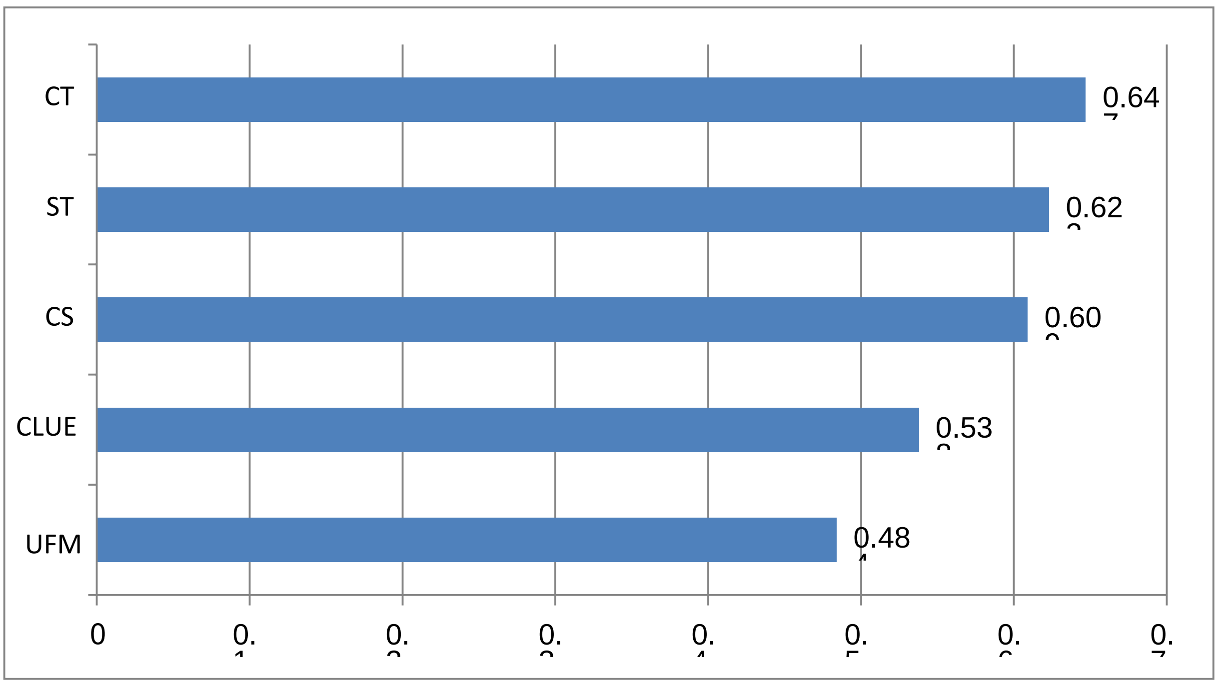

Figure 4. Five CBIR systems, averaged across all categories.

5. Conclusions

In this work, the performance of five unsupervised CBIR systems has been analyzed at varying precision levels. The two well-known systems, UFM & CLUE and three proposed Color-Shape, Color-Texture, and Shape-Texture are considered for analysis. All these approaches are based on graph-clustering (unsupervised learning) the algorithm, where, two visual trait values are clubbed together. The Color-Shape system is based on a combination of color and shape, Shape-Texture on shape & texture, and Color-Texture on color & texture. A weight is allocated to various images (as the target images) in the image repository with 70% features store of each visual trait. A bench-mark image database containing 1000 images is used. The Euclidean distance is used as the similarity metric for identifying the resemblance of images in the image database with a test image. It is observed that the CBIR models based on a combination of two visual features produce better performance in comparison to the other two mentioned models. The average precision value at varying levels of k has been taken by all three models viz. Color-Shape, Shape-Texture, and Color-Texture. It is also found that the Color-Texture system, in particular, outperforms other systems. Other clustering algorithms as well as systems based on a combination of more than two traits may also be developed and tested for accuracy improvement.

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