Content Based Image Retrieval Using Color and Texture Feature with Distance Matrices

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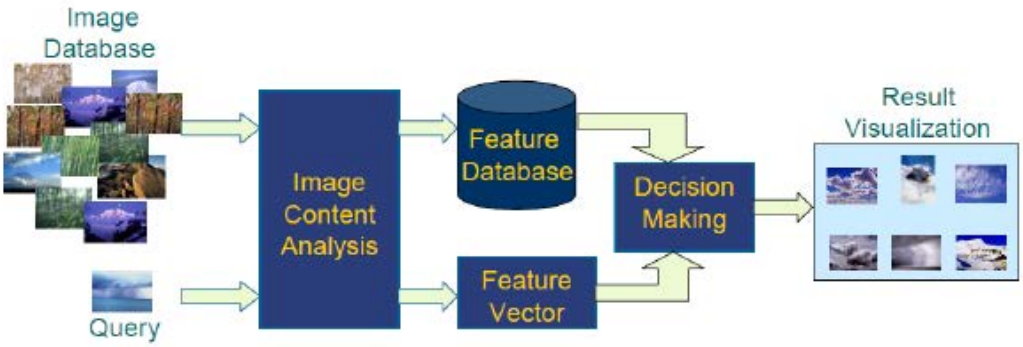
Abstract:Content based image retrieval is the task of retrieving the images from the large collection of database on the basis of their own visual content. In this paper, first I presented overview of geometric and statistical distance metrics used in CBIR along with the comparative analysis of these measures on color and texture features. Color features extracted by computing color histograms in HSV space and texture features by wavelet decompositions. Geometrical distances such as Euclidean, standard Euclidean statistical distance metrics such as spearman, minkowski, Mahalanobis were analyzed for feature similarity. Correlation and relative deviation is also found in it. I gave certain conclusions on the performance of all these distance metrics in terms of Precision and Recall graphs.

Keywords**:** CBIR, texture distance metrics, Euclidean, Mahalanobis, minkowski, spearman, correlation, deviation

1. INTRODUCTION

Content based image retrieval:Content-based image retrieval(CBIR), also known as query by image content(QBIC) and content-based visual information retrieval(CBVIR) is the application of computer visiontechniques to the image retrievalproblem, that is, the problem of searching for digital imagesin large databases."Content-based" means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself. CBIR is desirable because most web based image search engines rely purely on metadata and this produces a lot of garbage in the results.



Schematic Overview of the System

Image features categorized as low-level visual features, scale, rotation and translational invariant features and high-level semantic features. Low-level features include color, texture and shape. For general CBIR applications, color features are most important and are the intensity values of a pixel obtained in any color plane representation of an image. Color features obtained with the help of histograms, correlogram and color sets. Texture features capture the granularity and repetitive patterns of image surfaces and play an important role in image retrieval. Texture analysis is widely used in interpretation and classification of terrain images, radiographic and microscopic cell images.To some extent, performance of CBIR decided by the correct usage of distance metrics. Similarity measurement inCBIR can be rank based or distance based. Dissimilarity measures used in CBIR broadly classified as geometric measures and statistical measures. Dissimilarity measures for interval data are Minkowski distances. Similarity measures for interval data are Cosine and Pearson correlation distance metrics. Manpreet Singh, Sumit Chopra, Jagdeep Kaur.

2. LITERATURE SURVEY

Texture based image retrieval is done by Gabor filters represented in [7].Gabor filters are a group of wavelets. For a given image $I(x, y)$ with size $P \times Q$, its discrete Gabor wavelet transform is given by a convolution:

$$G_{mn}(x,y) = \sum_{s}\sum_{t} I(x-s, y-t)\psi^{*}_{mn}(s,t)$$

where, s and t are the filter mask size variables, and $\Psi^{*}mn$ is the complex conjugate of Ψmn.Color based image retrieval is done by color histogram color moments and hshvistogram.Minkowski distance metric at different levels presented in [3]. These metrics are preferred wheneach dimension holds equal importance in retrieval process. Minkowski metric used for feature vector comparison by An et al [4]. Manhattan distance or City block distance or Minkowski L1 depends on the rotation of the coordinate system, rather its translation L1 metric Minkowski distance to compare LBP histograms of query and database images [5]. Similarity of color histograms using L1 metric which is also known as city block metric proposed by Swain et al. Similarity of color histograms using L2 metric also known as Euclidean proposed in [2]. It was used for feature vector comparison. Minkowski L1, L2, Mahalanobis distance measures for shape databases evaluated in [6]. In this paper I presented image retrieval task based on HSV color histogram features and Gabor filter based texture features for analyzing the performance of standard geometrical, statistical and cumulative distance measures consisting Euclidean, Manhattan, Spearman, Mahalanobisdistances.

3. PROPOSED SYSTEM

Experimentation is done in Matlab to analyze the effect of distance metrics on different types of images.

1. Image database is loaded into Matlab workspace.
2. Query Image is selected from the database.
3. Color feature extraction is done by computing color histograms for query and database images in HSV Color space.
4. Using Gabor filters, texture features extracted.
5. Distance metrics were applied for feature similarity measurement.
6. Performance measures, precision (P) and recall (R) evaluated for the retrieved images.
7. Comparative analysis is done for image retrieval based on effect of similarity measures for color and texture features.

Image Dataset: 1000 images from 10 different categories where 100 images correspond to each category.

Feature Extraction: Concatenate the features to form 190-dimensional feature vectors.

Features	Description	Dimensions
Color histogram	HSV space is chosen, each H, S, V component is uniformly quantized into 8, 2 and 2 bins respectively	32
Color auto-correlogram	The image is quantized into 4x4x4 = 64 colors in the RGB space	64
Color moments	The first two moments (mean and standard deviation) from the R, G, B color channels are extracted	6
Gabor wavelet	Gabor wavelet filters spanning four scales: 0.05, 0.1, 0.2, 0.4 and six orientations: $\theta_0 = 0$, $\theta_{n+1} = \theta_n + \frac{6}{\pi}$ are applied to the image. The mean and standard deviation of the Gabor wavelet coefficients are used to form the feature vector	48
Wavelet moments	Applying the wavelet transform to the image with a 3-level decomposition, the mean and the standard deviation of the transform coefficients are used to form the feature vector	40

Image Similarity: There are many ways to define similarity. Similarity regarding color distribution, shapes, textures etc. Since the dataset is constructed from a combination of these features we need to define some similarity metrics to take advantage of it.

Euclidean Distance:
Euclidean distance is also called as L2 distance. If u=(x1, y1) and v=(x2, y2) are two points, then the Euclidean Distance between u and v is given as:

$$\sqrt{\sum_{i=1}^{N} (X_i - Y_i)^2}$$

Standard Euclidean distance:

$$d=\sqrt{\sum \left(\frac{1}{si^2}\right) (x_i - y_i)^2}$$

Manhattan Distance:
It is also called the L1 distance. If u=(x1, y1) and v=(x2, y2) are two points. Formula is given below:

$$\sum_{i=1}^{N} \frac{|X_i - Y_i|}{(1+X_i+Y_i)}$$

Spearman Similarity Measure:
If image intensities do not contain ties when they are ordered from the smallest to the largest, then by replacing the intensities with their ranks and calculating the Pearson correlation coefficient between the ranks in two images, Spearman rank correlation will be obtained. Spearman Rank Correlation measures the correlation between two sequences of values.

Mahalanobis Distance:

$$D_M(x) = \sqrt{(x-\mu)^T S^{-1} (x-\mu)}$$

Correlation Similarity Measure:-
In this case, similarity between two items i and j is measured by computing the *Pearson r* correlation corri,j. To make the correlation computation accurate we must first isolate the co-rated cases (i.e., cases where the users rated both i and j).

Relative Deviation Similarity Measure:-
The relative standard deviation (RSD) is useful for comparing the uncertainty between different measurements of varying absolute magnitude. The RSD is calculated from the standard deviation, s, and is commonly expressed as parts per thousand (ppt) or percentage (%):

$$RSD = \left(\frac{S}{\bar{x}}\right) * 1000 \; ppt \; \%$$

The %-RSD is also called the "coefficient of variance" or CV
Confusion matrix is used to compare the performance of the CBIR system using different distance metrics. To evaluate the overall performance of the CBIR system and compare the different distance metrics for retrieval accuracy, confusion matrix is calculated. A confusion matrix represents the actual classifications compared with the number of correct and incorrect prediction. The confusion matrix is n-by-n matrix, where n is the number of classes from the dataset. Each row represents the number of instances in actual class. Each column represents the number of instances in predicted class [9].

The other two are common evaluation methods namely 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. The precision and recall rates are computed by the following equations:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

4. EXPERIMENTS & RESULTS

I used WANG database for comparing CBIR system consisting ten different groups of images including Africa,flowers, dinosaurs, monuments, elephants, horses, beach, food,busses and mountains. We presented the comparative analysis of what distance metric performed well for a particular type of query for its color and texture features.

1. In first case I have used Euclidean as our Similarity metrics, following results are shown:-

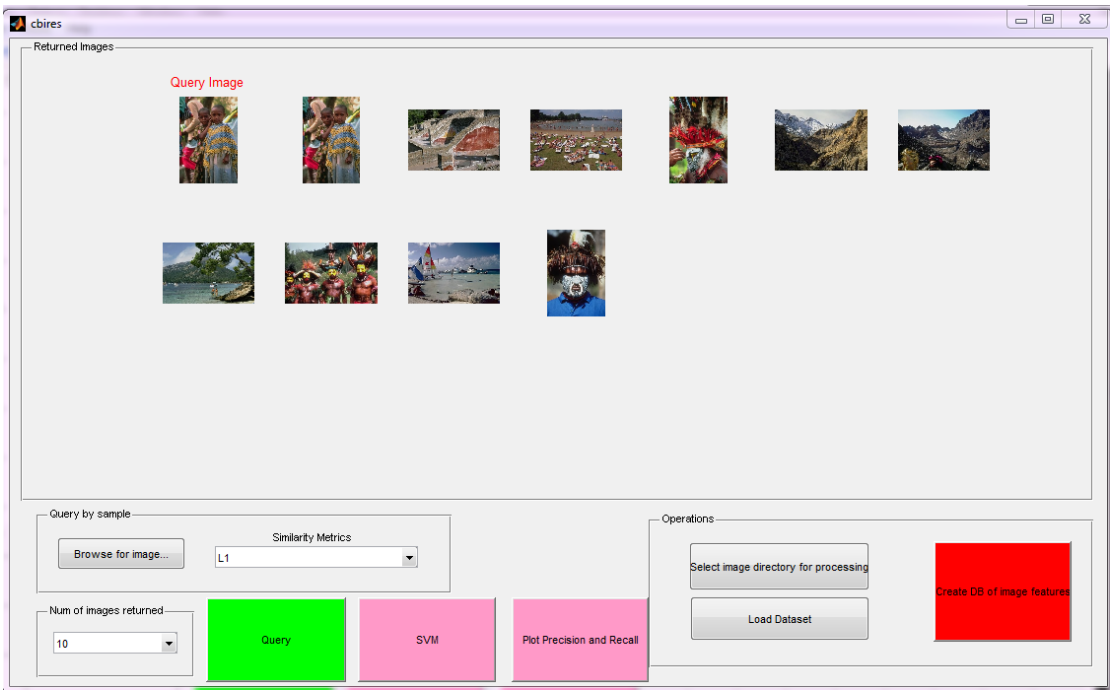


Fig 1 Retrieved images from database using L1 Similarity measure

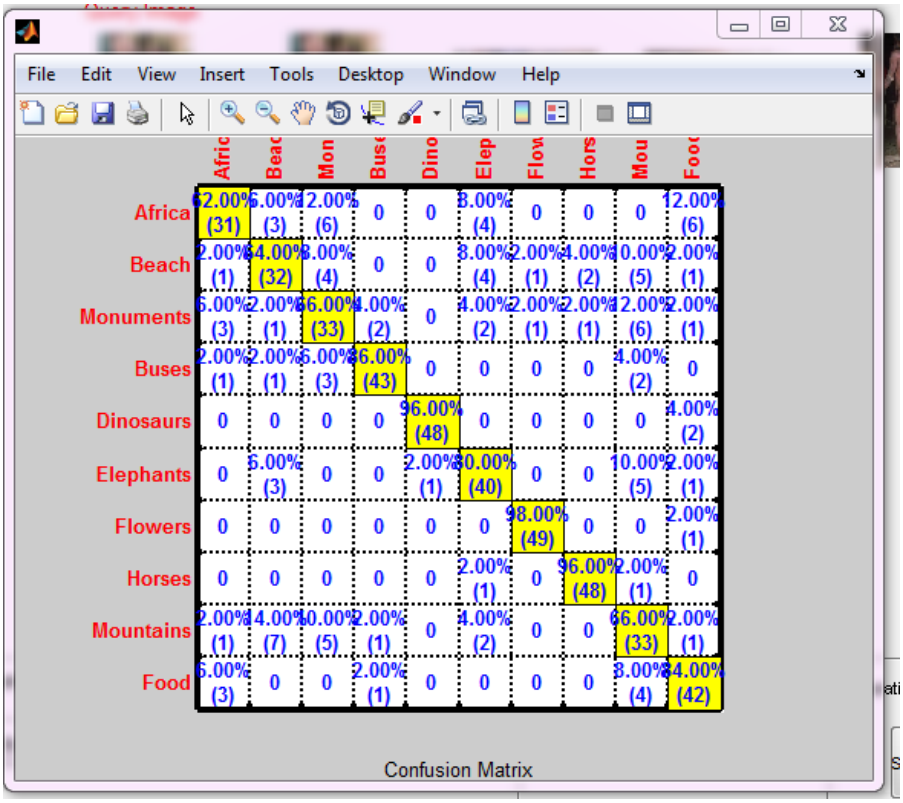


Fig 2 Confusion Matrix of L1 Similarity Measure

2. In second case I have used L2 distance as our Similarity metrics, results are shown below:-

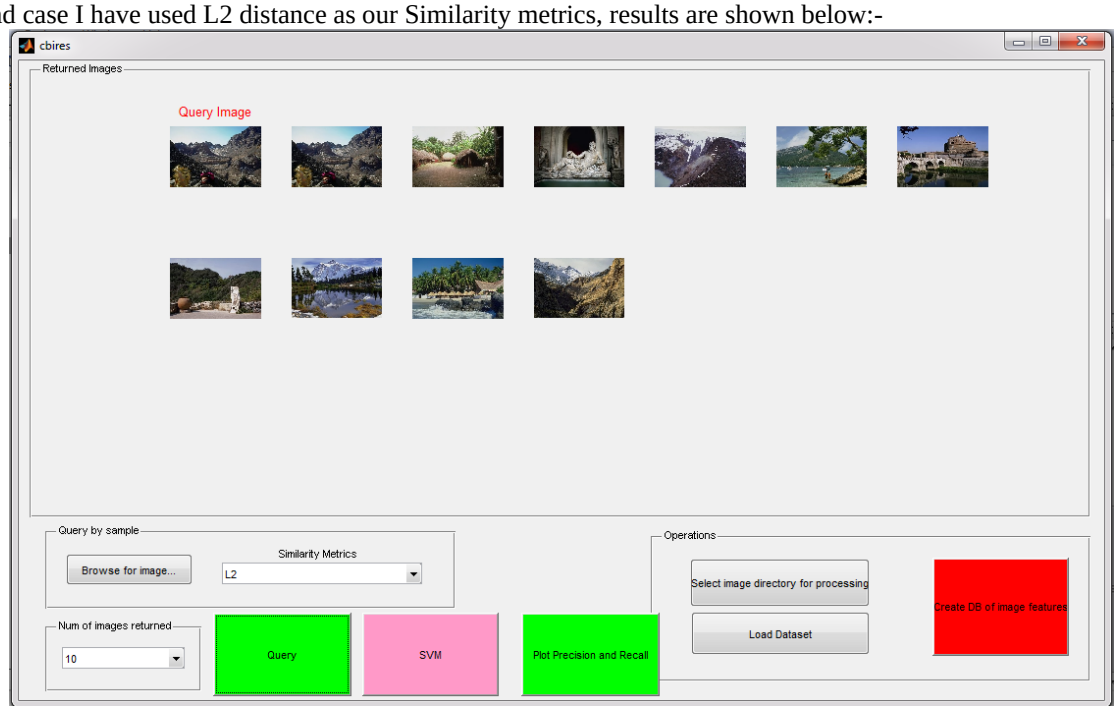
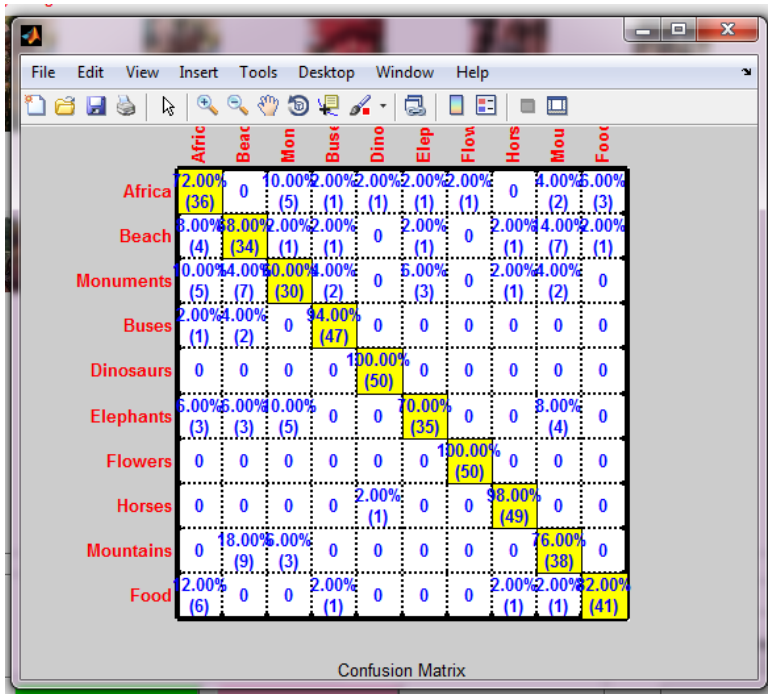


Fig 3 Retrieved images from database using L2 Similarity measure



	Afric	Beac	Mon	Buse	Dino	Elep	Flow	Hors	Mou	Foo
Africa	72.00% (36)	0	10.00% (5)	2.00% (1)	2.00% (1)	2.00% (1)	2.00% (1)	0	4.00% (2)	6.00% (3)
Beach	8.00% (4)	68.00% (34)	2.00% (1)	2.00% (1)	0	2.00% (1)	0	2.00% (1)	14.00% (7)	2.00% (1)
Monuments	10.00% (5)	14.00% (7)	60.00% (30)	4.00% (2)	0	6.00% (3)	0	2.00% (1)	4.00% (2)	0
Buses	2.00% (1)	4.00% (2)	0	94.00% (47)	0	0	0	0	0	0
Dinosaurs	0	0	0	0	100.00% (50)	0	0	0	0	0
Elephants	6.00% (3)	6.00% (3)	10.00% (5)	0	0	70.00% (35)	0	0	8.00% (4)	0
Flowers	0	0	0	0	0	0	100.00% (50)	0	0	0
Horses	0	0	0	0	2.00% (1)	0	0	98.00% (49)	0	0
Mountains	0	18.00% (9)	6.00% (3)	0	0	0	0	0	76.00% (38)	0
Food	12.00% (6)	0	0	2.00% (1)	0	0	0	2.00% (1)	2.00% (1)	82.00% (41)

Fig 4 confusion matrix of L2 similarity measure

3.In third case I standardized L1 have used distance as our Similarity metrics, results are shown below:-

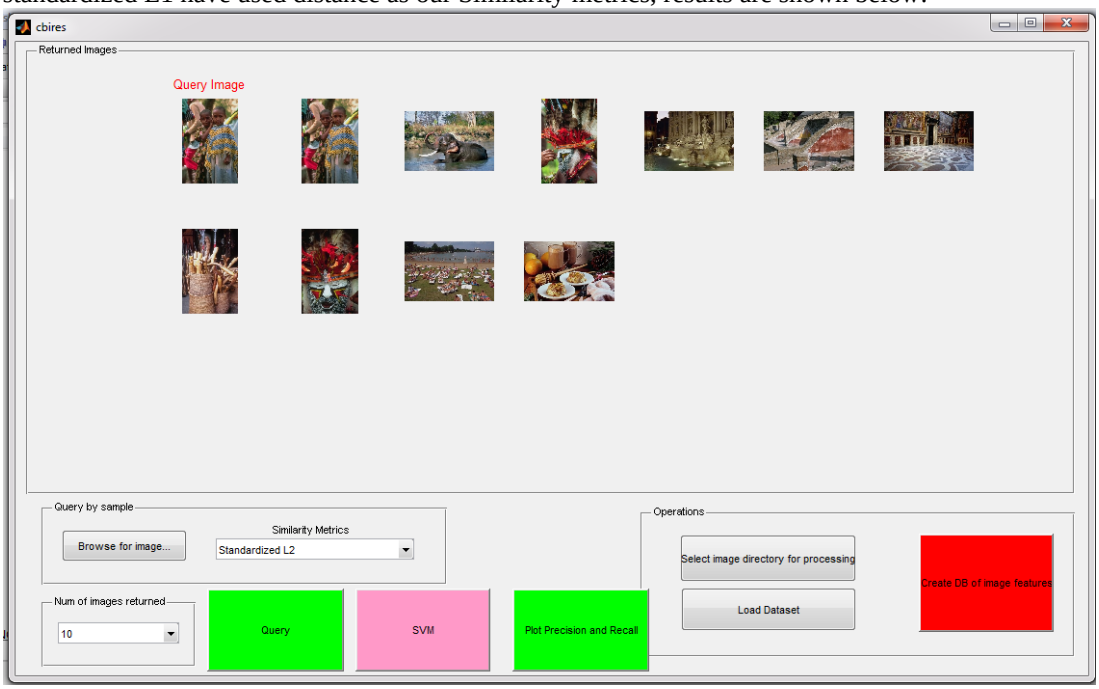
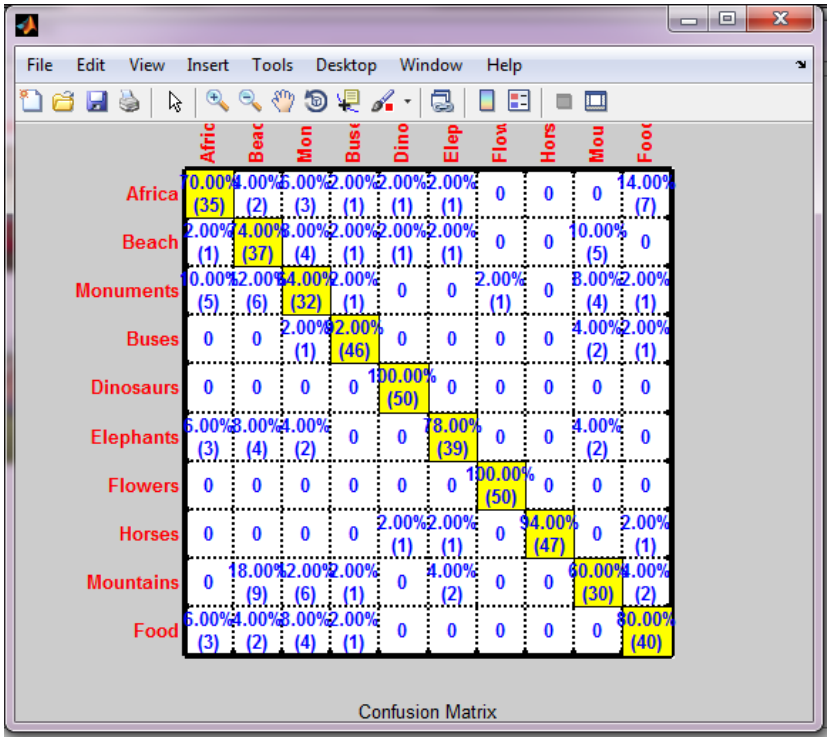


Fig 5 Retrieved images from database using standardized Similarity measure



	Africa	Beach	Monuments	Buses	Dinosaurs	Elephants	Flowers	Horses	Mountains	Food
Africa	70.00% (35)	4.00% (2)	6.00% (3)	2.00% (1)	2.00% (1)	2.00% (1)	0	0	0	14.00% (7)
Beach	2.00% (1)	74.00% (37)	8.00% (4)	2.00% (1)	2.00% (1)	2.00% (1)	0	0	10.00% (5)	0
Monuments	10.00% (5)	12.00% (6)	64.00% (32)	2.00% (1)	0	0	2.00% (1)	0	8.00% (4)	2.00% (1)
Buses	0	0	2.00% (1)	92.00% (46)	0	0	0	0	4.00% (2)	2.00% (1)
Dinosaurs	0	0	0	0	100.00% (50)	0	0	0	0	0
Elephants	6.00% (3)	8.00% (4)	4.00% (2)	0	0	78.00% (39)	0	0	4.00% (2)	0
Flowers	0	0	0	0	0	0	100.00% (50)	0	0	0
Horses	0	0	0	0	2.00% (1)	2.00% (1)	0	94.00% (47)	0	2.00% (1)
Mountains	0	18.00% (9)	12.00% (6)	2.00% (1)	0	4.00% (2)	0	0	60.00% (30)	4.00% (2)
Food	6.00% (3)	4.00% (2)	8.00% (4)	2.00% (1)	0	0	0	0	0	80.00% (40)

Fig 6 confusion matrix of standardized similarity measure

2. In forth case, I have used Relative Deviation distance as our Similarity metrics, results are shown below:-

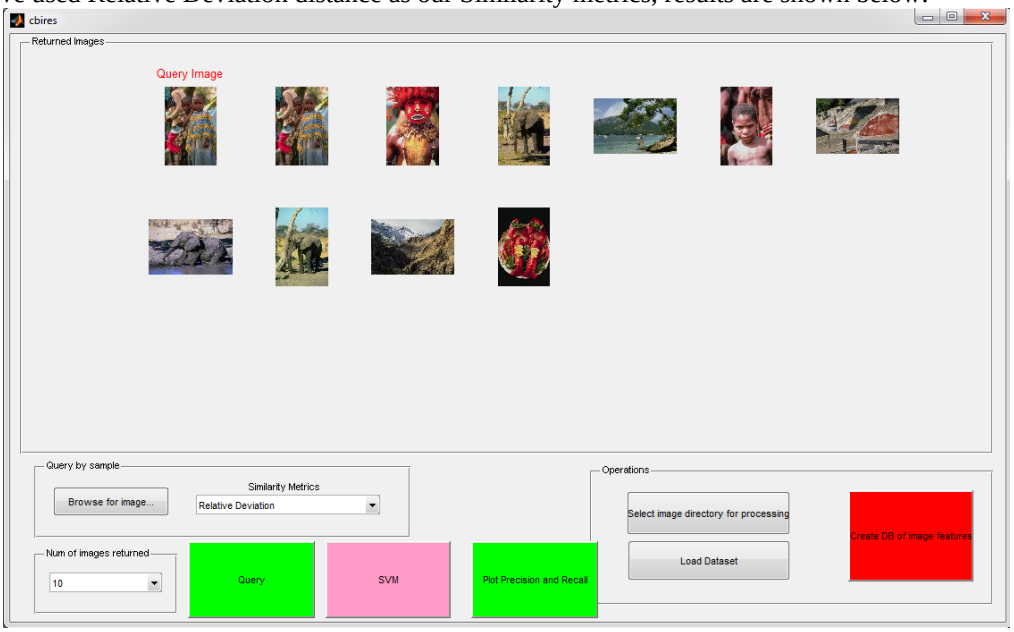


Fig 7 Retrieved images from database using Relative Deviation Similarity measure

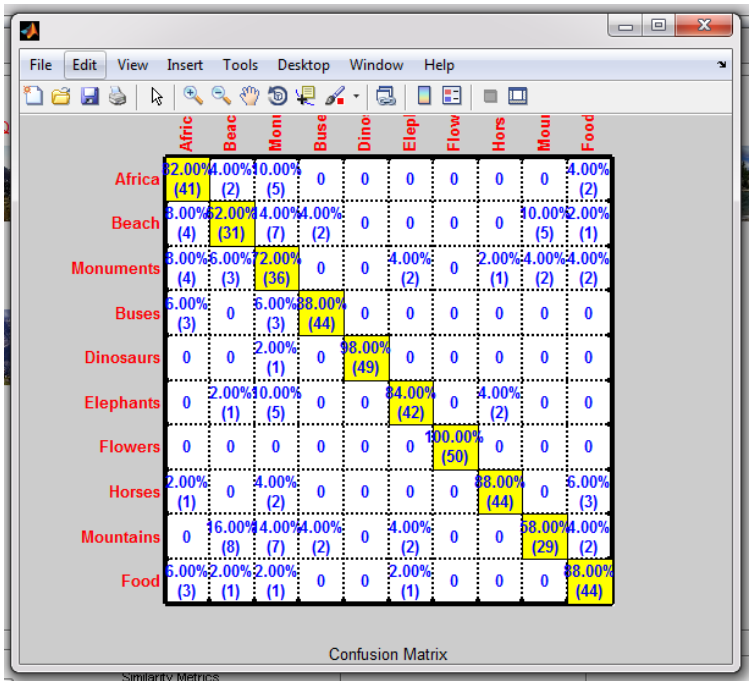


Fig 8 confusion matrix of Relative Deviation Similarity Measure

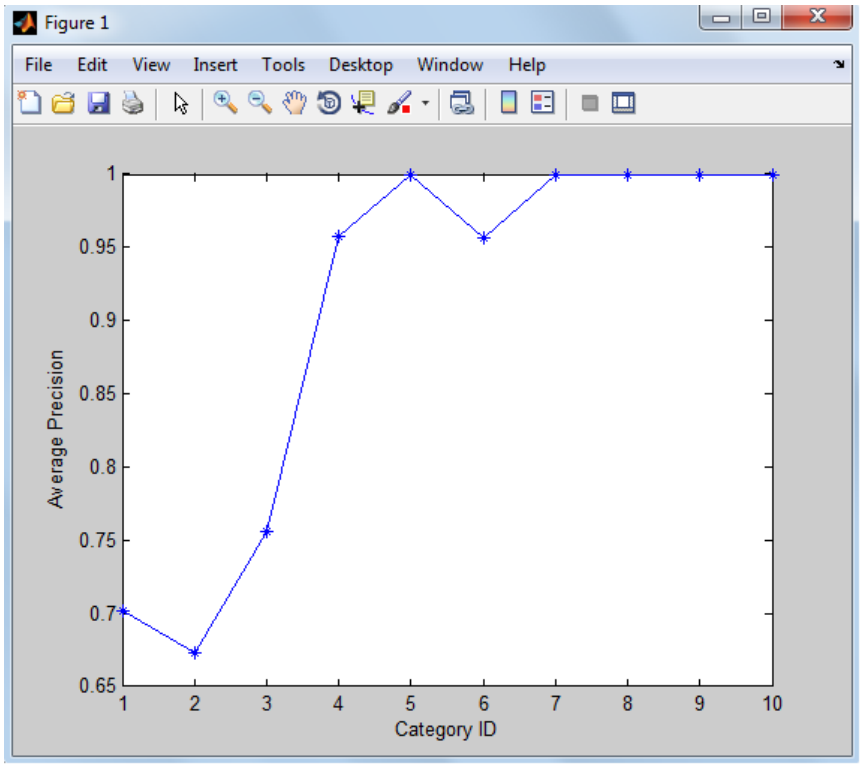


Fig 9 Precision Graph of Relative Deviation Similarity Measure

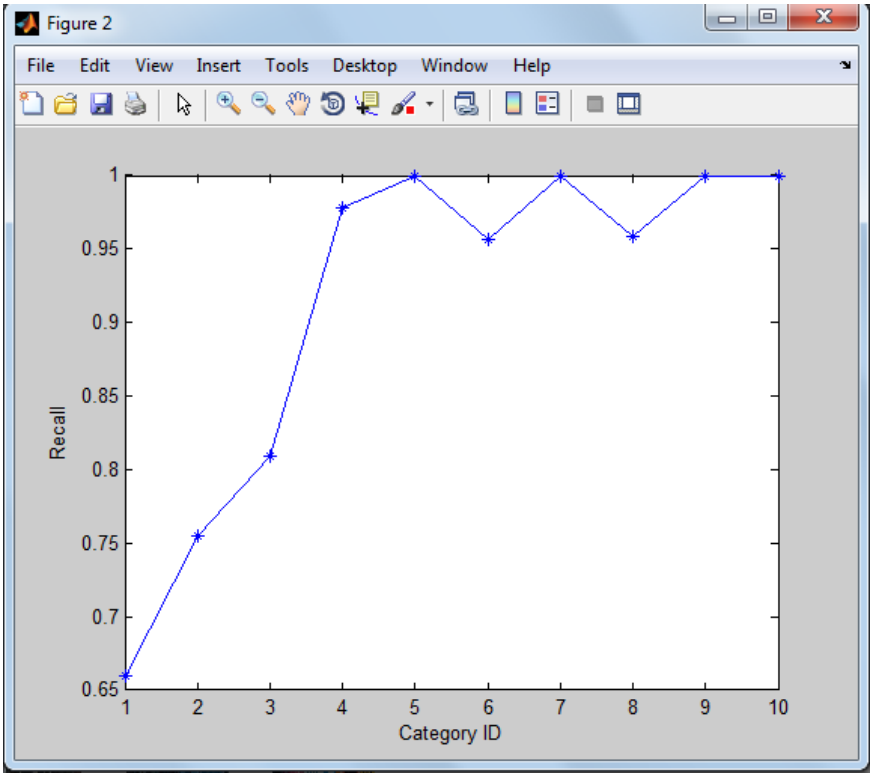


Fig 10 Recall Graph of Relative Deviation Similarity Measure

5. In fifth case I have used correlation distance as our Similarity metrics, results are shown below:-

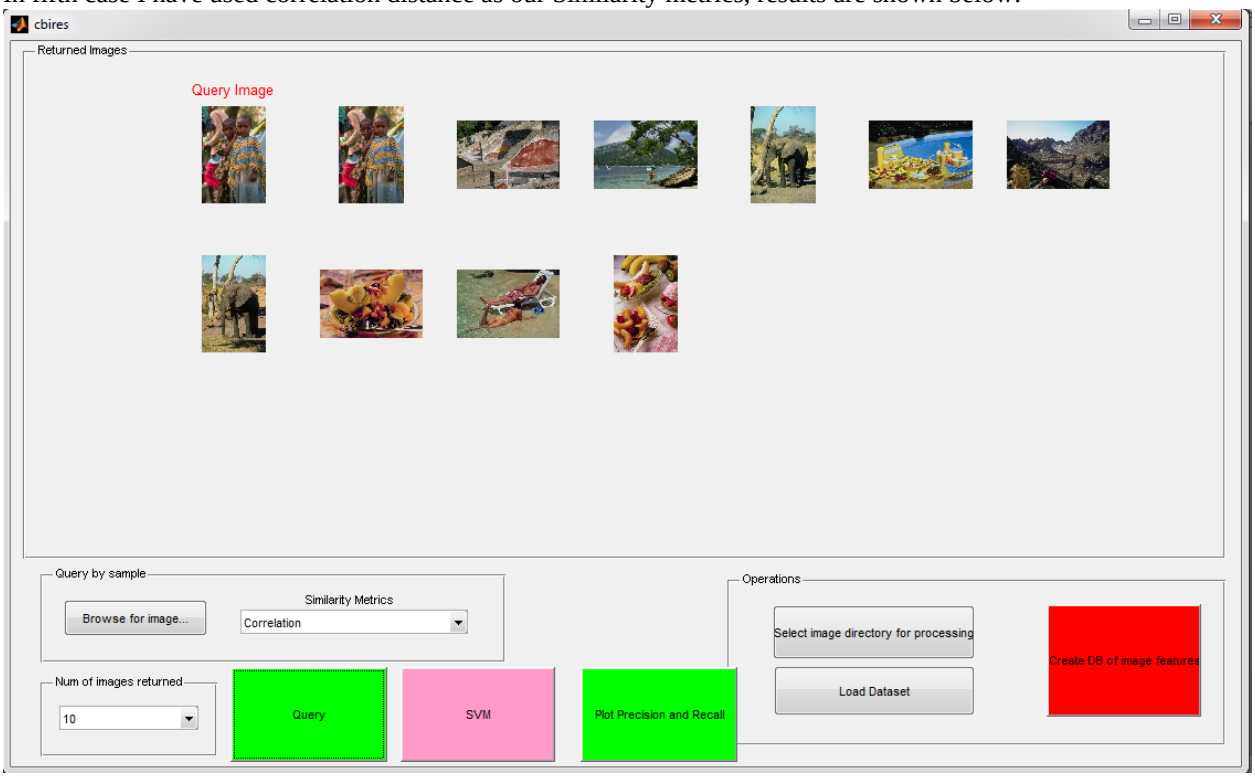


Fig 11 Retrieved images from database using Correlation Similarity measure

	Africa	Beach	Monum	Buses	Dinosa	Elepha	Flowers	Horses	Mounta	Food
Africa	78.00% (156.2095)	0	8.00% (16.0215)	0	2.00% (4.0054)	6.00% (12.0161)	0	0	4.00% (8.0107)	2.00% (4.0054)
Beach	4.00% (8.0107)	74.00% (148.1987)	4.00% (8.0107)	2.00% (4.0054)	0	0	0	0	14.00% (28.0376)	2.00% (4.0054)
Monuments	8.00% (16.0215)	8.00% (16.0215)	70.00% (140.188)	2.00% (4.0054)	0	2.00% (4.0054)	0	2.00% (4.0054)	6.00% (12.0161)	2.00% (4.0054)
Buses	4.00% (8.0107)	4.00% (8.0107)	2.00% (4.0054)	84.00% (168.2256)	0	0	0	0	6.00% (12.0161)	0
Dinosaurs	0	0	0	0	96.00% (192.2578)	0	0	0	4.00% (8.0107)	0
Elephants	6.00% (12.0161)	2.00% (4.0054)	4.00% (8.0107)	0	0	78.00% (156.2095)	0	2.00% (4.0054)	8.00% (16.0215)	0
Flowers	0	0	0	0	0	0	100.00% (200.2686)	0	0	0
Horses	0	0	0	0	0	2.00% (4.0054)	0	94.00% (188.2524)	4.00% (8.0107)	0
Mountains	0	16.00% (32.043)	10.00% (20.0269)	2.00% (4.0054)	0	0	0	0	72.00% (144.1934)	0
Food	10.00% (20.0269)	2.00% (4.0054)	2.00% (4.0054)	2.00% (4.0054)	2.00% (4.0054)	0	0	0	0	82.00% (164.2202)

Confusion Matrix

Fig 12 Confusion Matrix of Correlation Similarity Measure

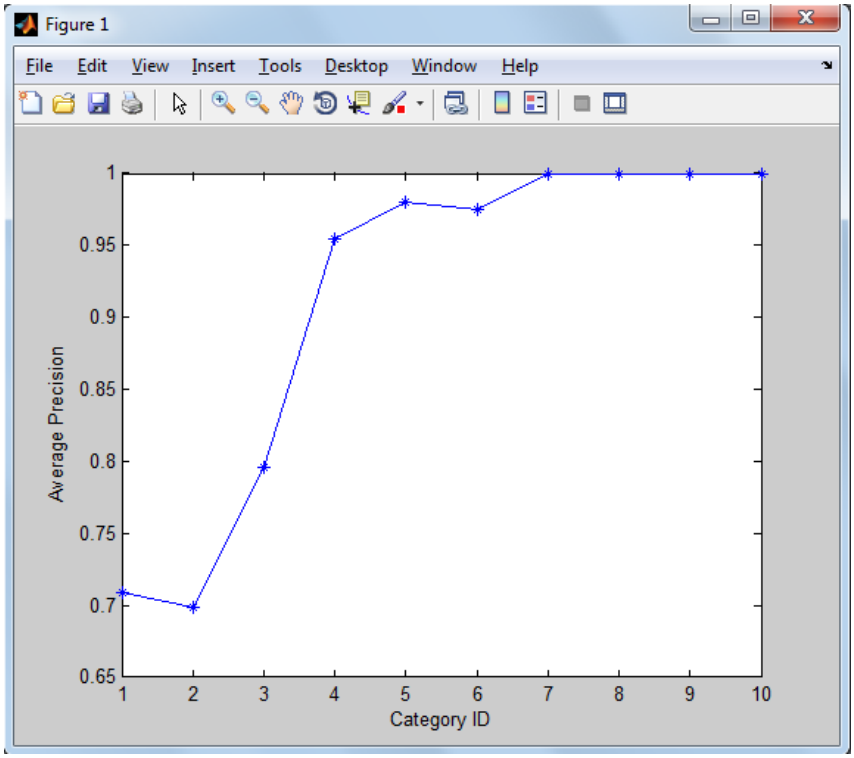


Fig 13 Precision Graph of Correlation Similarity Measure

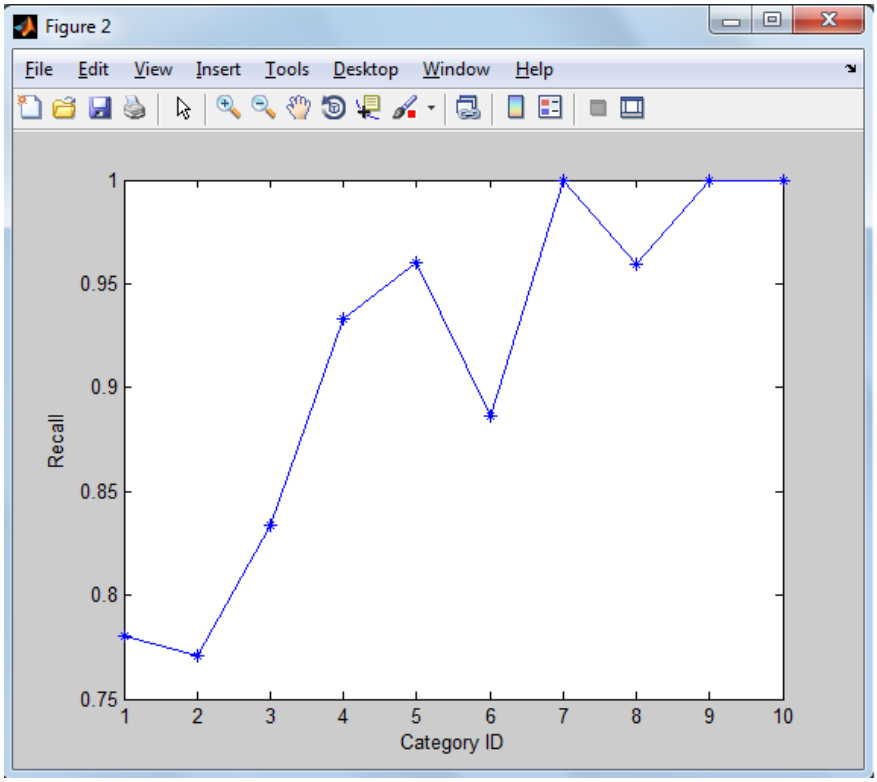


Fig 14 Recall Graph of Correlation Similarity Measure

5. Conclusion

In this paper, an algorithm has been proposed to retrieve image from database which are matched with query image. I have used eight distances L1,L2, Standardized L1,normalized L2, minkowski, spearman, Correlation and Relative Deviation as our similarity metrics. The performance of the system is shown in the form of Confusion matrix and recall and precision graphs.

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