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A New Enhanced Relevance Feedback in Cbir Using Hierarchical Unsupervised Niche Clustering Approach

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ABSTRACT

Content Based Image Retrieval (CBIR) is a technique that utilizes the visual content of an image such as color, texture, shape etc., for retrieving similar images from large-scale image databases. However, due to the semantic gap between low-level visual features and high-level concepts of image, CBIR cannot achieve satisfactory performance. Relevance feedback (RF) has been introduced as a power tool to involve the user in the system to improve the performance of CBIR. This paper proposes a new method, Navigation Pattern Based Relevance Feedback (NPRF) using Hierarchical Unsupervised Niche Clustering Approach (HUNC), which capture the user's intention by discovering the navigation pattern from the users browsing behaviors. The objective of NPRF is to expand one search point to several search points by combining the navigation patterns and the Relevance Feedback Search algorithm. HUNC is a divisive hierarchical version of a robust clustering approach that uses a Genetic Algorithm to evolve as population of candidate solutions through generations of competition and reproduction. Extensive experiments on a real-world image database demonstrate the effectiveness of the proposed scheme in improving the performance of CBIR by exploiting the Hierarchical Unsupervised Niche Clustering Approach over the conventional navigation pattern approaches.

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INTRODUCTION

The Interest in the potential of digital images has increased enormously over the last few years and fuelled at least in part by the rapid growth of imaging on the World-Wide Web. The users in many professional fields are exploiting the opportunities offered by the ability to access and manipulate remotely-stored images in all kinds of new and exciting ways. However, they are also discovering that the process of locating a desired image in a large and varied collection can be a source of considerable frustration. The image retrieval techniques are becoming wider and the solutions have become an increasingly active area for research and development. During the past decade, remarkable progress has been made in both theoretical research and system development.In Text based image retrieval, searching is based on keywords and text described by human's conception (Kato,T., 1992). It focuses on text rather than looking into the content of an image. There are certain problems in textual based retrieval systems such as costly manual annotation and improper automated annotation. These drawbacks may lead to unsatisfactory results in semantic image search. To overcome these issues, several potential image retrieval algorithms have been evolved for the past few years (Christopher, C., Yang, 2004; Muwei Jian, Shi, 2008). Content Based Image Retrieval(CBIR) is the foundation of current image retrieval techniques. In CBIR the images are represented using low level image features such as color, texture and shape. These traditional image retrieval methods compute the similarity between user's query and database images using Query by example (QBE) technique (Vu, K., 2003). Even though the search strategies become powerful, it is very difficult optimize the retrieval quality of CBIR within a single query process. To address this issue, the relevance feedback (RF) mechanism has been incorporated in QBE system (Zhang, R., Z. Zhang, 2004).

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1.1 Relevance Feedback:

Relevance feedback is a continual interaction process between the user and system. The user selects the favoured images to improve the image retrieval process repeatedly until the user satisfaction is achieved. Despite many Relevance Feedback Techniques (Qin, T., 2008; Smith, J.R. and S.F. Chang, 1996; Chih-Chin Lai, 2011) developed on CBIR systems, there are some common problems, namely redundant browsing and exploration convergence. In most of the RF methods concentrate on capturing user satisfaction in one query process. The query refinement is performed repeatedly by analyzing the precise positive images preferred by the user. Exclusively for the complex images the users have gone through a long series of feedbacks to retrieve the desired images. The problem of exploration convergence is demonstrated with an example. Suppose that two user submit a same query image consist of “tree” and “water”. But the users aimed concepts are “tree” and “water” respectively. After a few number of feedbacks for query and query 2, two different moving paths has been produced with aimed concepts respectively. This is called visual diversity problem. It is very difficult for a traditional CBIR system to capture the user’s intension when a query image consists of compound concepts e.g., tree and water. To solve these drawbacks Navigation pattern based Relevance feedback Technique is combined with RF.

1.2 Navigation pattern based Relevance Feedback (NPRF):

Navigation pattern based Relevance Feedback search combines two query refinement strategies, which includes query point movement and query expansion to solve the problem of exploration convergence. User’s browsing pattern can be captured using navigation pattern mining. It comprises of two main steps namely construction of

Navigation transaction table and generating navigation pattern mining. Navigation transaction table contains number of iterations and corresponding items from which valuable navigation pattern has been constructed using Apriori algorithm. Through NPRF method user’s intension can be obtained using implicit navigation pattern and achieved optimal results in a short number of feedbacks.

The outline of this paper is organized as follows. Section 2 reviews the related works. Section 3 illustrate the framework of proposed Navigation pattern based Relevance Feedback (NPRF**).** Section 4 demonstrates the Experimental results and performance of the proposed model. Finally, Section 5 concludes this presentation.

Related Works:

Sangoh Jeong *et al*.(2003) presented the image retrieval based on color histogram Gauss mixture vector quantization approach. This method is extensively suited for image retrieval problems . It makes use of color histogram for feature extraction and also used quantization technique for RGB color space.

D.H. Kim and *et al*., (2003) formulated the Relevance Feedback method Using Adaptive Clustering for Content based image Retrieval. This approach makes use of adaptive classification and cluster merging to form the multiple clusters for a complex image query. It obtained the accurate retrieval results regardless of the shapes of clusters of a query. This method attained better precision and recall than the query expansion method.

X. Jin and *et al*., (2004) explained the image retrieval using multiple queries. This method retrieve the relevant images using relevance feedback mechanism and visual clusters by combining the results of multiple queries. At each iterations the user select the positive examples and generate the new query center. A multi-query retrieval strategy (called a multipoint query) has been utilized to collect the scattered results.

Steven C.H. Hoi[2006] introduced log based relevance feedback mechanism in content based image retrieval. It combined the log data of user feedback with relevance feedback technique. It utilized novel learning algorithm to address the log based relevance feedback problem. The proposed method achieved better results in improving the performance of conventional relevance feedback mechanism.

Haiyu Song and *et al*., (2010) discussed the segmentation based Adaptive feature selection and extraction approaches in image retrieval. Query image is segmented using Gaussian Mixture Models (GMM) then the R,G,B color space and HSV color space components are extracted and quantized.

Md Mahmudur Rahman(2011) presented a novel learning based and classification image retrieval approach for medical image collection. It utilized the relevance feedback mechanism to update the feature weight based on positive user feedback. The proposed retrieval framework performance has been experimented with large medical database and achieved better results.

Yi Yang, Feiping Nie(2012) Explained a new approach for multimedia content based image image retrieval. It comprises of two algorithms namely semi supervised ranking with Local Regression and Global Alignment (LRGA) to learn a Laplacian matrix for data ranking. For each data point a linear regression model is used to calculate the ranking score of its neighboring points. Then a semi-supervised long-term Relevance Feedback (RF) algorithm has been used to refine the multimedia data representation.

Motivation:

There are many relevance feedback mechanism had been implemented in interactive content based image retrieval. But it still have some standing problems like redundant browsing and exploration convergence. The main objective of existing RF approach is to gain the user's satisfaction in one query process. But it makes the user to go on many iterations to for complex and compound images and also capture the user's intension. To overcome these issues the Navigation pattern based relevance feedback(NPRF) using Hierarchical Unsupervised Clustering algorithm has been introduced.

Proposed Method:

The proposed method integrates relevance feedback techniques and navigation pattern approach to achieve optimized search results. The overall process of the system is illustrated in Fig 1. The proposed model comprises of the following phases (i) Initial query phases (ii) Image Search Phase (iii) Knowledge discovery Phase (iv) Data storage phase.

In Initial query phase, the user submitted query image as input to the system . The system extract color, texture and shape features[20] from query image as well as image database. The similarity is measured using Euclidean distance between query image and data base images. The top ranked images are displayed for the user as an initial feedback. The positive examples are selected by the user provide valuable information to the image search phase. Then new query point is calculated using Roccio formula[26] from positive examples then k nearest images to the new query point is computed using query expansion method. User browsing pattern can be captured in knowledge discovery phase using data transformation and navigation pattern mining method. The data storage phase act as a knowledge mart and consist of image features and navigation pattern. Finally, RF Techniques and knowledge discovery results are merged and return the desired images for the user. The search procedure is repeated until user satisfaction is achieved.

3.1 Initial query processing phase:

It consist of various stages namely feature extraction, similarity matching and image retrieval

3.1.1 Feature Extraction:

For an query image, the proposed method extracts color feature using Histogram technique [24], texture feature is extracted using Gabor filter [25] and Edge Orientation Histogram algorithm is used for extracting shape features of an image.

Color based image retrieval:

Input: Query Image.
Output: Similar Color Images.
Step 1. Convert RGB color space image into HSV color space.
Step 2. Color quantization is carried out using color histogram by assigning 8 level each to hue, saturation and value to give a quantized HSV space with 8x8x8=512 histogram bins.
Step 3. The normalized histogram is obtained by dividing with the total number of pixels.
Step 4. Repeat step 1 to step 3 on an image in the database.
Step 5. Calculate the similarity matrix of query image and the image present in the database.
Step 6. Repeat the steps from 4 to 5 for all the images in the database.
Step 7. Retrieve the images.

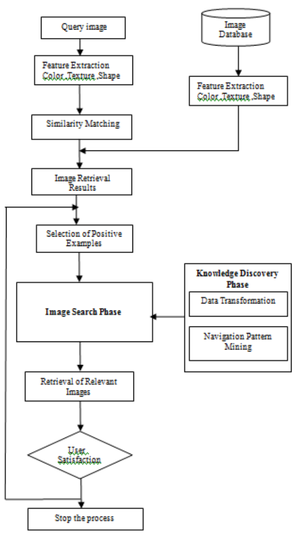

Fig. 1: Overview Of Proposed NPRF approach.

Texture based image retrieval:

Texture is defined as differences in the spatial arrangement of gray values of neighboring pixels and is an important visual feature in image segmentation

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and scene understanding. Gabor filter is mostly adopted for extracting the texture features from the images for its retrieval [3].Texture features are extracted by subjecting each filtered image to nonlinear transformation and computing measure energy in a window around each pixel.

Input: Query Image from the Wang's dataset:
Output: Similar Texture Images that match to a given query image:
Step 1. Gabor filter is applied on image with different orientation at different scale then the array of
magnitude obtained.

$$E(m.n) = \sum xy \left| Gmn\ (x,y) \right|, \quad [1]$$

m=0,1...M-1;n=0,1...N-1
Where m,n denote the scale and orientation gabor wavelet.
Step 2.Homogeneous texture feature is measured using μ_{mn} and σ_{mn}

$$\mu mn = \frac{E(M,N)}{PXQ} \quad [2]$$

$$\sigma mn = \frac{\sqrt{\sum xy \left| (Gmn\ (xy) \right| - \mu mn)2}}{PXQ} \quad [3]$$

Where μ_{mn} denote mean and σ_{mn} represent standard deviation.
Step 3. Feature vector fg is created using μ_{mn} and σ_{mn} as follows
$f_g=\{ \mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots \mu_{m-1,n-1}, \sigma_{m-1,n-1}\}$ [4]
Step 4. Feature vector is computed for each image in the database and query image stored as feature vector database. The similarity is measured using Canberra distance measure and top ranked images are retrieved to the user.

Shape based image retrieval:
Edge Orientation Histogram Algorithm
Input: Query Image from the Wang's dataset
Output: Similar Shape Images that match to the given query image.
Step 1. Create a histogram of an edge type for a query image and divided into 4 × 4 rectangular nonoverlapping regions
Step 2. Edge of an image is identified using canny edge detector operator.
Step 3. Resultant feature histogram is computed for each image and represented using 4 × 4 × 5 matrix.
Step 4.The normalized Edge Orientation Feature histogram used as a feature vector for similarity matching.
Step 5.The similarity between query image and database images are measured using Hausdr off distance and relevant images are retrieved.

3.1.2 Similarity Matching:

In color based image retrieval the similarity between the histogram of a query image and image database is measured using Euclidean distance formula. For texture and shape based retrieval Mahalonobis Distance and Hausdroff distance metrics has been utilized.

Euclidean distance:

Let D (I, J) be the distance measure between the query image I and the database image J and f_i(I) is the number of pixels in bin i of I .

$$D(I,J) = (\sum_i | f_i(I) - f_j(J) |^p)^{1/p} \quad [5]$$

When p=1, 2 and ∞, D (I, J) is the L1, L2 (called as Euclidean distance) and L∞ distance respectively.

Mahalanobis distance:

The gabor feature vector of query image (I) and database images (J) are compared using Mahalanobis distance metric given

$$D(I,J) = \sqrt{(F_I - F_J)^T C^{-1} (F_I - F_J)} \quad [6]$$

where C is the covariance matrix of the feature vectors.

The Hausdroff distance:

In shape based image retrieval method the similarity of query image with database images are measured using Hausdroff distance method.

Given two finite points sets A={a1,....ap} and B={b1...bq) the Hausdroff distance is defines as
H(A,B)=max(h(A,B),h(B,A)) [7]
Where h(A,B)=max min‖a-b‖ [8]
a€A b€B
and ‖.‖ is some underlying norm on the points of A and B.

3.2 Image Search Phase:

NPRF search combine the image search phase and knowledge discovery base to expand one search point into multiple search point for achieving optimized retrieval results. Image search phase comprises of two modules such as query point generation and Query expansion.

3.2.1 Query Point Generation:

Image retrieval phase display the retrieval results by extracting color, texture and shape feature. In order to generate new query point the user has to select positive examples from retrieval results.
Input: Positive Examples
Output: Query point Generation
Step1: Set of positive examples chosen by the user. G = { g1,g2,g3. . .gk }
Step2: Extract d dimension of the ith feature from positive examples $F_i = \{ f1^x..f2^x..f3^x..fd^x \}$
Step 3: New query point is generated using equation [1]
qnew= { F1,F2,F3,...Fb } where 1< i< b
Step 4: Store positive examples and querpoint qpnew to the log database.

Query Expansion:

To solve the problem of exploration

convergence ,query expansion refinement strategy has been incorporated in image retrieval process. it identified the positive and negative query seed for each positive and negative example using k nearest neighbour search technique. Finally set of matching leaf node can be found by traversing the navigation pattern tree.

3.3 Knowledge Discovery Phase:

The user's desire can be accurately captured in two stages namely data transformation and navigation pattern mining. When all positive examples considered for navigation pattern mining, it is very hard to find all frequent itemset which cause mining cost more expensive. Query transformation uses query point dictionary technique to reduce the items in the transaction database. In navigation pattern mining user's browsing pattern can be captured using Apriori algorithm.

3.3.1 Data Transformation:

In Query Point Dictionary(QPD) approach iterations are represented ITN={Q,Iteration 0,iteration 1,Iteration 2,Iteration n} Where Q contains the set of starting query images. For each iteration the visual query points are grouped into several cluster by means of Hierarchical clustering algorithm and named as c11,c12,c13,c1m finally the query points of each cluster are assigned a specific symbol or item no.

H-UNC Clustering Algorithm:

H-UNC is a dissenting robust clustering approach (Un-supervised Niche Clustering (UNC)) that uses a Genetic Algorithm (GA). This algorithm deals with the data that contains noise and it can automatically determine the number of clusters. HUNC algorithm is not fixed the number of cluster in advance. It does not require analytical derivation of the prototypes and also uses specific similarity measures based on user's desired pattern .

Input: Query Image

Output: Cluster Representative

1. Create a randomly generated population of N individuals.

2. Test each individual within the problem space and assign a measure of fitness. $f_i = \frac{\sum_{j=1}^{N} w_{ij}}{\sigma_i^2}$ Where $w_{ij} = \exp - \frac{d_{ij}^2}{2\sigma_i^2}$ and σ_i^2 is the robust measure of scale dispersion for the i^th cluster, d_{ij}^2 be the Euclidean distance from data point x_j to cluster center C_i

3. Selection phase: Select a pair of individuals from the population with probability based on their fitness.

4. Apply crossover at some randomly selected point along each individual.

5. Apply mutation to each new individual.

6. Place the new individual in the new population.

7. Replace the old population with the new population.

8. Test if target termination criteria are met, such as a specified best fitness value; else repeat from step 2.

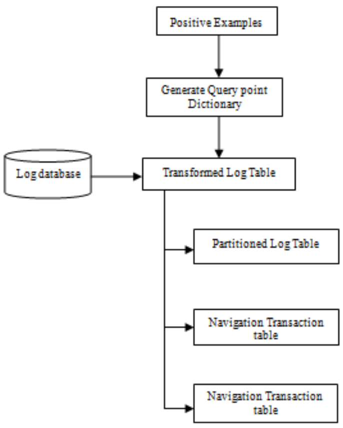

Fig. 2: Transformed Log table.

Once a query point is projected onto QPD item no stored into transformed log table. It is further split into three tables namely navigation transaction table, Partitioned Log table and QP table . namely navigation transaction table is used for navigation pattern mining is shown in Fig.2. and Table 1&2

3.3.2 Navigation Pattern Mining:

User's common interest attained by discovering navigation pattern using Apriori algorithm. It consist of two stages as construction of transaction table and Generation of Navigation Pattern. E G.

Construction of Transaction Table:

Transaction table composed of Query session id and corresponding item_no .Randomly five query sessions are chosen from original log table.

Table 1: Navigation Pattern Generation.

Item	Count	Frequent itemset
C11	2	1-itemset
C12	2	
C21	3	
C32	4	
C42	3	
C11, C32	2	2-itemset
C11, C42	2	
C12, C21	2	
C11, C32, C42	3	3-itemset

Apriori Algorithm:

Input: Original Log Database

Output: A set of Navigation Patterns

1. A frequent itemset is an itemset whose support is larger than some user-specified minimum support (denoted M_k ,where k is the size of the itemset).
2. A candidate itemset is a potentially frequent itemset (denoted C_k, where k is the size of the itemset).

Pass 1

1. Form the candidate itemsets in C_1
2. Save the frequent itemsets in M_1

Pass k

1. Generate the candidate itemsets in C_k from the frequent itemsets in M_{k-1}
2. Combine M $_{S-1}$p with M_{S-1}q, as follows: insert into C_S .
3. Select p.item$_1$, p.item$_2$, . . . , p.item$_{k-1}$, q.item$_{k-1}$ from M_{S-1} p, M_{S-1}q
Where p.item$_1$= q.item$_1$, . . . p.item$_{S-2}$ = q.item$_{S-2}$, p.item$_{S-1}$< q.item$_{S-1}$
4. Generate all (S-1)-subsets from the candidate itemsets in $C_{S.}$
5. Prune all candidate itemsets from C_S where some (S-1)-subset of the candidate itemset is not in the frequent itemset M_{S-1}
6. Scan the transaction database to determine the support for each candidate itemset in C_S .
7. Save the frequent itemsets in M_S .

3.3.2 NPRF search Algorithm:

The objective of NPRF is to expand the one search point to multiple search points by combining the navigation patterns and the NPRF Search algorithm

Input: A set of positive examples picked up by the user and set of Navigation Patterns

Output: A set of relevant images

1. A new query point is generated using query Point Movement(QPM) by
2. averaging the visual features of positive examples using Rocchio formula

$$Q_i = Q_{i-1} + \alpha \sum_{j=1}^{nr} R_j / nr - \beta \sum_{j=1}^{nir} IR_j / nir \qquad [9]$$

where Qi is the vector of the ith query,
Rj is the vector of the jth relevant image,
IRj is the vector of the jth irrelevant image,
nr is the cardinality of relevant images, and nir is the
cardinality of irrelevant images.

3. Store query point and positive examples into the log database.

The query item in each navigation pattern is called a query seed. For each query seed find the navigation pattern tree by determining the nearest query seeds(root) using query Expansion Technique.

4. Find the nearest leaf nodes from the matching navigation pattern tree.
5. Find the top most relevant visual query points from the set of nearest leaf nodes.
6. The top most relevant images are returned to the user.

Experimental Results:

The experiments are conducted using Matlab 7.10.0 on an Intel PentiumD 2.0GHz processor with 2GB memory. The CBIR technique is tested on the Wang's dataset of 1005 variable size images spread across 5 categories of Bus, Dinosaur, Elephant, Flowers, Horse, etc as shown in Fig 3.

Fig. 3: Wang's dataset.

Feature Extraction and Retrieval Results:

The user chooses one of the image from wang's dataset as a query image shown in fig.3.The proposed system extract color, texture and shape feature from query image. The color histogram of a query image is shown in fig.4 and texture, shape feature extraction is given in fig.5 and fig.6 respectively.

Fig. 4: Query Image.

For each image a 3-D histogram of HSV values are calculated. Euclidean distance is widely used to match the stored histograms with the histogram of an query image for retrieving similar images.

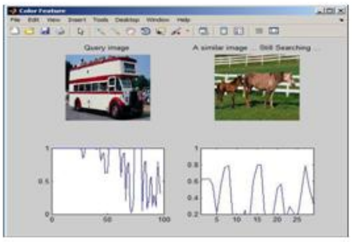

Fig. 5: Color histogram of a query image.

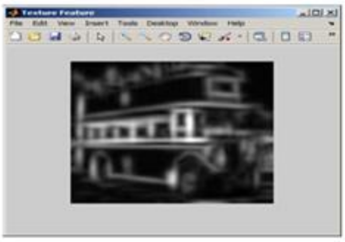

Fig. 6: Texture Feature of QueryImage.

Fig. 7: Shape Feature Extraction for a query image.

The Retrieval results by combining color, texture and shape features are shown in fig.7.User marks the positive examples from the retrieval results as shown in Fig.9.It gives a valuable information for query refinement and knowledge discovery.

The user marks images as relevant by looking at each image, and the set of relevant images are grouped to develop clusters, that are closest in match to the query image by using K Means algorithm. and Hierarchical Unsupervised Clustering Algorithm . In each feedback, results are presented to the user and related browsing information is stored in the log database. Retrieval results are given in Fig 10 .NPRF using HUNC results are given in Fig.11

Fig. 8: Image Retrieval results using Color, Texture and Shape Features.

Fig. 9: Positive Samples.

Fig. 10: NPRF Retrieval results using K Means.

Fig. 11: NPRF Retrieval results using HUNC.

To analyze the effectiveness of our proposed approach Precision and Coverage value for NPRF with K Means and NPRF with HUNC are computed using equation [11] and equation [12].

$$Precision = \frac{|Correct|}{|Retrieved|} * 100\% \quad [9]$$

$$Recall = \frac{ac\_correct}{Relevant} * 100\% \quad [10]$$

where correct is the positive images picked by the user at each iteration, retrieved is the resulting image set extracted by the proposed approach at each feedback, ac_correct is the group of all correct during a query session, and relevant is the ground truth. The criterion precision delivers the ability for hunting the desired images in user's mind is tabulated in Table 2 and Table 3. It can be observed that the proposed NPRF with HUNC achieve approximately 89% of average precision. But the existing NPRF with K Means method achieves 79% of average precision at iteration 5. The average Precision and Coverage value for NPRF with K Means and NPRF with HUNC is shown in Table 4, Table 5.

Fig 12 and Fig.13 Shows the graph illustrating the retrieval performance of proposed system with Existing method in terms of average precision and Recall values

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Table 2: Precision Values of NPRF with K Means.

Category	NPRF with K Means Precision Values				
	Iteration1	Iteration2	Iteration3	Iteration4	Iteration5
Bus	0.4	0.45	0.5	0.6	0.7
Elephant	0.45	0.6	0.65	0.7	0.75
Flower	0.6	0.7	0.75	0.8	0.95
Horse	0.3	0.4	0.45	0.55	0.6
Dinosaur	0.45	0.5	0.65	0.8	0.9

Table 3: Precision Values of NPRF with HUNC.

Category	NPRF with K Means Precision Values				
	Iteration1	Iteration2	Iteration3	Iteration4	Iteration5
Bus	0.4	0.5	0.55	0.75	0.85
Elephant	0.45	0.65	0.7	0.75	0.85
Flower	0.6	0.65	0.7	0.75	0.85
Horse	0.3	0.45	0.5	0.65	0.75
Dinosaur	0.45	0.75	0.8	0.9	1.0

Table 4: Precision and Coverage Values of NPRF with K Means.

Categories	NPRF with K Means	
	Precision	Coverage
Bus	0.75	0.53
Flower	0.6	0.76
Elephant	0.65	0.46
Horse	0.7	0.63
Dinosaur	0.5	0.64

Table 5: Precision and coverage values of NPRF with HUNC.

Categories	NPRF with HUNC	
	Precision	Coverage
Bus	0.85	0.61
Flower	0.75	0.81
lephant	0.8	0.53
Horse	0.8	0.68
Dinosaur	0.9	0.73

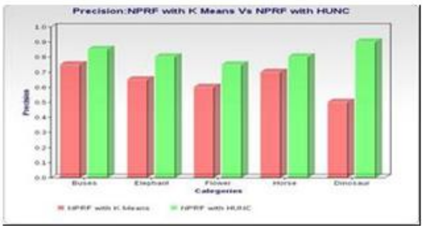

Fig. 12: Comparison of NPRF with K Means Vs NPRF with HUNC in terms of Coverage.

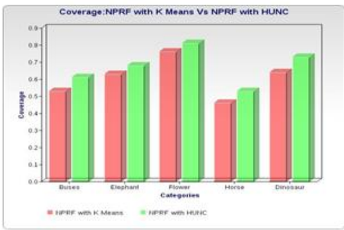

Fig. 13: Comparison of NPRF with K Means Vs NPRF with HUNC in terms of Coverage.

Conclusion:

This paper presents a novel method called Navigation Pattern Based Relevance Feedback (NPRF)using Hierarchical Unsupervised Niche Clustering Approach (HUNC)in interactive CBIR Systems. The main objective of NPRF is to efficiently optimize the retrieval results of CBIR technique. The proposed NPRF search algorithm utilized query refinement strategy namely Query Point Movement using HUNC method and also K Means Clustering Algorithm .Along with Query refinement strategy Navigation Pattern mining is merged to obtain the user intension more accurately. As a result conventional problems such as visual diversity and exploration convergence are rectified. The Experimental results show that the proposed NPRF search is very effective in terms of precision and coverage. Within a few iterations the navigation pattern helps the user to obtain a global results.

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