# Distributed Content based Image Retrieval using Navigation Pattern with Relevance Feedback

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## ABSTRACT
The image retrieval applications are designed to fetch required images from the image databases. Images are searched using textual query or images. The textual query based retrieval is performed with image annotations. The image features are used in the content based image retrieval process on the image database provides huge collection of images. Query image features are compared with the database image features. The similarity measures are used to select relevant images from the databases. Relevance feedbacks are collected from the users at the time of query processing. The feedbacks are maintained under the image database and used in subsequent image retrievals. The navigation pattern based relevance feedback model is limited with accuracy and scalability factors. So the content based image retrieval scheme is enhanced to perform image retrieval in a distributed parallel manner and clustering techniques are used to improve the speed and accuracy of image retrieval. This is achieved through a multiscale approach. A quantitative measure is suggested for segmentation evaluation. The goal is to impute the missing data in the presence of edges or boundaries and recover the image. Their performance is compared with another method that imputes the missing values using edge-preserving spatial smoothers with locally varying weights. The proposed system first detects onset and offsets, and then generates segments by matching corresponding onset images.

## Keywords
Image-mining,Navigation Pattern mining, Cluster Analysis, Edge detection, Object Recognition, Relevance Feedback.

## 1. INTRODUCTION
Multichannel signal processing has been the subject of extensive research during the last ten years, primarily due to its importance to color image processing. The amount of research published to date indicates a great interest in the areas of color image filtering and analysis. It is widely accepted that color conveys information about the objects in a scene and that this information can be used to further refine the performance of an imaging system. Color images are studied in this paper using a vector approach. The value at each image pixel is represented by a three-channel vector, transforming the color image to a vector field in which each vector's direction and length is related to the pixel's chromatic properties [1]. Being a two-dimensional (2-D), three-channel signal, and a color image requires increased computation and storage, as compared to a grey-scale image during processing. The notion of scale gives an important hint to texture analysis. To date, image and video storage and retrieval systems have typically relied on human supplied textual annotations to enable indexing and searches however, can never capture the visual content sufficiently. Real-world images (e.g., natural scenes) are however with noise, complex backgrounds, or object occlusions, etc. The texture and shape features are therefore far from adequate and are limited to deal with only a small fraction of the real-world images [2]. We therefore propose a new feature set called *structural features* of which one can think as features *in-between texture and shape*.

The text-based indexes for large image and video archives are time consuming to create. They necessitate that each image and video scene is analyzed manually by a domain expert so the contents can be described textually, and the texture captures spatial distribution of illuminance variations and typically pays attention only to repeating patterns. Shape represents a specific edge feature that is related to object contour [16]. Neither of them pays attention to information represented in non-repeating illuminance patterns in general, which is the category we want to define the structural features to represent.

## 2. PROCEDURE OF IMAGE RETRIVAL
This section covers the details regarding identify a subset of structural features, namely *edge/structural features*, and provide an algorithm for fast and efficient extraction. Even though it is possible for one to argue that there is no clear conceptual boundary between structure and texture or shape features, structural features. As a result, a number of powerful image retrieval algorithms have been proposed to deal with such problems over the past few years. Content-Based Image Retrieval (CBIR) is the mainstay of current image retrieval systems. In general, the purpose of CBIR is to present an image conceptually, with a set of low-level visual features such as color, texture, and shape [3].

It is very difficult to optimize the retrieval quality of CBIR within only one query process. The hidden problem is that the extracted visual features are too diverse to capture the concept of the user's query. To solve such problems, in the QBE system, the users can pick up some preferred images to refine the image explorations iteratively. The feedback procedure, called Relevance Feedback (RF), repeats until the user is satisfied with the retrieval results.

## 3. IMAGE RETRIVAL FRAME WORK
### 3.1 Specification
In many image retrieval systems can be conceptually described by the framework depicted in figure (1). In this article, we survey how the user can formulate a query, whether and how relevance feedback is possible, what kind of features are used, how features from query image and data base image are matched, how the retrieval results are presented to the user, and what indexing data structures are used. The user interface typically consists of a query formulation part and a result presentation part. Specification

of which images to retrieve from the database can be done in many ways [19]. One way is to browse through the database one by one. Another way is to specify the image in terms of keywords, or in terms of image features that are extracted from the image, such as a color histogram. To provide an image or sketch from which features of the same type must be extracted as for the database images, in order to match these features.[8] A nice taxonomy of interaction models is given in Relevance feedback is about providing positive or negative feedback about the retrieval result, so that the system can refine the search.

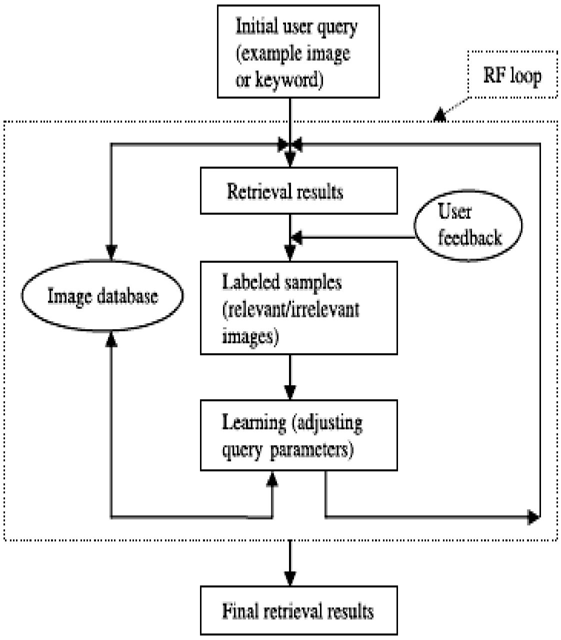


Fig.1. Image retrieval Frame Work Model for Comparing Reference and Proposed algorithms

These consider several classes of features that are used to specify queries: color, texture, shape, spatial layout, and faces. Color features are often easily obtained directly from the pixel intensities, and the color histograms over the whole image, over a fixed sub image, or over a segmented region are often used the notion of texture generally refers to the presence of a spatial pattern that has some properties of homogeneity[10]. In particular, the homogeneity cannot result from the presence of only a single color in the regions, but requires interaction of various colors.

## 3.2 Subtraction of Patterns

With the appropriate metadata, current CBIR systems can achieve retrieval by colour, texture, by shape and spatial relationship. In fact, usage mining has been made on how to generate users' browsing patterns to facilitate the web pages retrieval. Similarly, for web image retrieval, the user has to submit a query term to the search engine, so-called textual-based image search the user can obtain a set of most relevant web images according to the metadata or the browsing log.
However, if the result does not satisfy the user, the query refinement can be easily incorporated into the query procedure [5,11]. For instance, users can specify the colour feature query by choosing relative amounts of red, green, and blue or by selecting a desired colour from a colour palette. Also, users can choose the desired texture for the texture feature query and draw a sketch for the shape feature query. Sometimes when querying by example image, we are not interested in whole image but just some parts or objects.

Also, it may not be concerned about the location of objects. For instance, in the case of an image of Green Mountain with a sunrise, we might want to retrieve images with only a sunrise. We do not care whether the sunrise is over a green mountain or a blue sea and we do not care whether the sunrise is on the left top of the image or in the right middle of the image. In other words, the process involves sub-image or object retrieval.

## 3.3 Submission of Similarity Measures

This section describes the similarity measures used for matching visual information and the approaches taken to improve similarity results. The similarity is determined as a distance between some extracted feature and a vector that combines these. The most common scheme adopted is the use of histograms which are deemed similar if their distance is less than or equal to a preset distance threshold. Some of the common histogram comparison tests are described here. In other cases, the features are clustered based on their equivalency which is denoted as the distance between these features in some multi-dimensional space [7].

## 3.4 Review of Color Features

All characteristics of the LAB color space that could be exploited in extracting color features from a digital image. Converting an image from RGB to LAB results in the luminance or intensity of that image being represented on the axis named *L* that is perpendicular on a pile of *ab* planes, each one containing all the possible colors for a given luminance [6, 7].

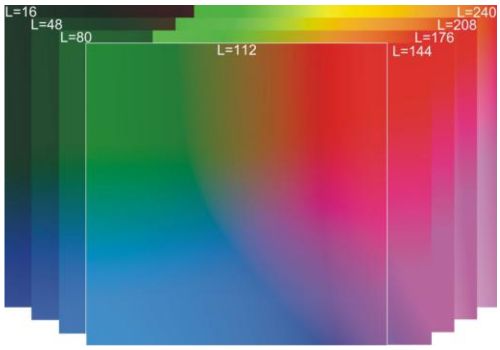


Fig.2.ColorDistribution of Luminance

While the values of the coordinates *L*, *a* and *b* are real numbers when applying RGB to LAB mathematical conversion [4], for programming convenience these values are mapped to integers from 0 to 255, gray levels from each RGB color plane. In the equation 1, we get the values of the coordinate points of color distribution from each segmented image partition as shown in the ab plane.

$$D = \sum_{i=0}^{n} \binom{n}{k} x^k \ b^n \ a^{n-k} \qquad \ldots\ldots\ldots (1)$$

. A color is defined by a point ($a1$, $b1$) in the *ab* plane of a given luminance *L* [5]. Colors are changing uniformly as we move gradually apart from this point. The LAB color space was designed so that the human eye perceives this gradual change of color as a uniform one. Multi-class feedback builds upon the concept of Cluster feedback by providing more than one cluster (sets) of Feedback images. These sets typically represent images belonging to different classes that a user has predicted [7]. Multiclass feedback is basically the usual nearest-neighbor classification that is used frequently in pattern recognition. In Equation 2, the multi-resolution compositing technique is to turn into an image which is a combination of an original image and a colour and synthetic texture derived from target; the combination is controlled by a mask [20].

$$D(x\,b_{int}) = a_0 + \sum_{n=1}^{\infty}\left(a_n \min\frac{n\pi x}{L} + b_n \min\frac{n\pi x}{L}\right) \ldots\ldots\ldots \quad (2)$$

The algorithm remains the same as before, except that in the iterations of the algorithm, the original is composite back into the noise image according to the mask using that avoids blurring and aliasing.

### 3.5 Texture

In uniform textures, the textures within a region may vary randomly in orientation and the position and shape of the textures may be perturbed by the end of the algorithm, noise will have been converted into a synthetic texture. First, Match-Histogram is used to force the intensity distribution of noise to match the intensity distribution of target. Then an analysis is constructed from the target texture. The pyramid representation can be chosen to capture features of various sizes by using [11], [13] features of various orientations. Then, the noise is modified in an iterative manner. At each iteration, a synthesis is constructed from noise, and Match-Histogram is done on each of the sub-bands of the synthesis and analysis.

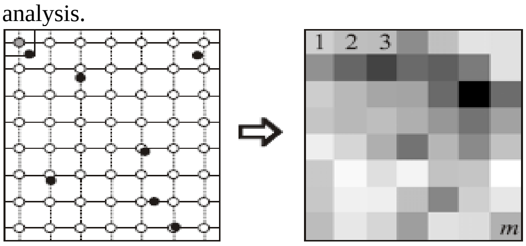


Fig.3. Synthesized Image Transformation for Pixel Similarity

In similar way apply to implement the algorithm for reconstruction. Neighborhoods from the sub-band images and with the same centre coordinates are represented [8]. The distance between two neighborhoods is then given by the difference in magnitude between the two vectors representing them. In order to avoid problems with boundary conditions, it is necessary to pad each sub image with zeros before performing the algorithm. This padding should be removed prior to inverse transform.

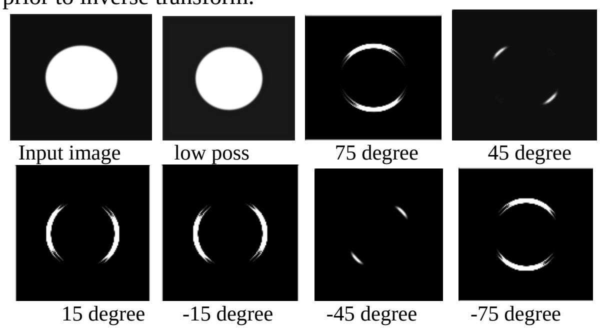


Fig.4. Synthesized Image Transformation for Similar Texture

Using a high amount of classes causes connected components to be very small, which results in nearly no computed sub textures. The feature matching synthesis technique of pixel shows the result. In all cases, the pre-processing time required only once for a given texture is below m*n this includes segmentation, texture-mesh generation and sub texture field synthesis [16].

## 4. SHAPE FUTURE

Shape and texture features are extracted from query image, and then *m*-nearest classes to the query image are determined by the semantic classifier. Similar images in the search space are sorted by similarity measure and presented to user.

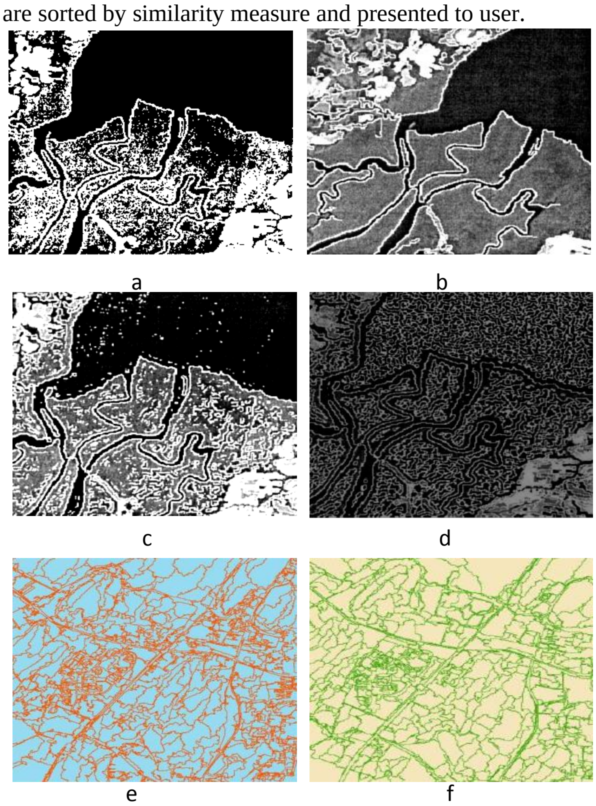


Fig.5. Region Extraction. (a)Closed Contour Detection, (b) Edges of Sorted Contour (c) Edges Removed by Region Extraction (d) Edges from Improved Measures (e) Resolution Segmentation (f) RegionFeedback.

Positive and negative images in the presented images are labeled by user, and then used to improve the retrieval performance by a RF algorithm [4,12].In the following, more details of this framework are described. For example, if a query image corresponds to the retrieved images at the first level using the shape feature are as shown in Fig .5. It is noted that the retrievals using only shape information consists of different colours but similar shapes. The proposed scheme for indexing the still texture content is employed on the image database. Global texture features are extracted from the entire image, the extracted texture features are then used to measure the similarity between images for computational efficiency, the samples were analysed using horizontally and vertically projected one-dimensional profiles [15, 17].

### 4.1 Algorithm

As already described above, NPRFSearch is proposed to reach the high precision of image retrieval in a shorter query process by using the valuable navigation patterns. In this section, we explain the details of NPRFSearch [9]. The NPRFSearch algorithm is triggered by receiving: 1) a set of positive examples G and negative examples N determined by the user at the preceding feedback, 2) a set of navigation patterns TR = {tr1, tr2, . . . , trh}, where each trh contains a query seed $r^{th}$ and several patterns and 3) an accuracy threshold thrd. In brief, the iterative search procedure can be decomposed into several steps as follows:

1. Generate a new query point by averaging the visual features of positive examples.
2. Find the matching navigation pattern trees by determining the nearest query seeds (root).

3. Find the nearest leaf nodes (terminations of a path) from the matching navigation pattern trees.
4. Find the top s relevant visual query points from the set of the nearest leaf nodes.
5. Finally, the top k relevant images are returned to the user.

Input: A set of positive examples G-$\cup$ gt picked up by the user, a set of negative example N=$\cup$ nu, a set of navigation patterns TR= {tr1, tr2,…..trh}, and an accuracy threshold thrd;
Output: A set of the relevant images R;
Algorithm NPRF Search
Generate a new query point qpnew by G and compute the new feature weights by Equationn3;
Let NIMG be the accumulated set of negative examples, and NIMG=NIMG $\cup$ N;
Store qpnew and G into the log database;
Initialize each trh.rth.chk=0 and CanPnt=$\phi$ ;
for each gt $\in$ G do
Determine the special query-seed rth with the shortest distance to gt ,where rth $\in$ Q;
rth.chk = 1;
End for
If $\frac{|G|}{|G \cup N|} < thrd$ then
For each nu $\in$ N do
Determine the special seed rth with the shortest distance to nu, where rth $\in$ Q and Q $\subseteq$ TR;
Count (rth) ++;
End for
Find the seed rth with max (count(rth));
rth.chk = 0;
End if
For each trh do
If trh.chk=1 then
Find the set of the visual query points QPT within the leaf-nodes of pattern trh;
CanPnt=CanPnt $\cup$ QPT; /* CanPnt indicates the set of the accumulated candidate query points*/
End if
End for
Find the top s visual query points SQPT = {sqpt1, sqpt2,,…… sqpts} similar to qpnew from CanPnt;
For i=1 to s do
Find the positive image set RIMG in the transformed log table, which is referred to sqpt;
CanImg=CanImg $\cup$ RIMG; /* CanImg indicates the set of the relevant images*/
End for
CanImg= {CanImg\NIMG};
Rank the images in CanImg;
Return the set if top k similar images R;

## 4.2 Association Rule of Extraction

An association rule discovery algorithm searches the space of all possible patterns for rules that meet the user-specified support and confidence thresholds. The problem of discovering association rules can be divided into two steps: Find all item sets whose support is greater than the specified threshold[14,18]. Item sets with minimum support are called frequent item sets. Generate association rules from the frequent item sets. To do this, consider all partitioning of the item set into rule left-hand and right-hand sides. Confidence of a candidate rule X-Y is calculated as support (XY) / support (X). All rules that meet the confidence threshold are reported as discoveries of the algorithm.

$L_1$: = {frequent 1-itemsets};
k:= 2; // k represents the pass number
While ($L_{k-1}$)
Ck = New candidates of size k generated from $L_{k-1}$
For all transactions $t \in D$ Increment count of all candidates in $C_k$
That is contained in t
$L_k$ = All candidates in $C_k$ with minimum support
k = k+1
Report $U_k$, $L_k$ as the discovered frequent item sets.

## 4.3 Image Defect Detection

They also investigated defect detection using only imaginary Wavelet functions as an edge detector. For computational efficiency [3], the samples were analysed using horizontally and vertically projected one-dimensional profiles. Defects were localised by thresholding the filtering responses from an unseen image sample based on the mean and standard deviation of template filtering responses. Performed automatic scale selection to preserve channels with maximum energy and directional information. In multiscale local wavelet filtering is a novelty detection framework [5,15].

## 4.4 Sub image Classification

Existing region or object-based systems rely on segmentation [2,7] or require that the region of interest occupy a large portion of the entire image [19]. This facilitates fast retrieval but causes these systems to fail when accurate segmentation is not possible or when the object occupies a small portion of the database image. Additionally, most existing techniques discriminate based on a histogram of color or texture features computed over the entire region.

# 5. CLASSIFICATION OF RELAVANCE FEEDBACK

Region-Based matching is a difficult problem because of inaccurate segmentation. Semantically precise image segmentation is extremely difficult and is still an open problem in computer vision [12]. For example, segmentation algorithm can segment a dog into two regions: the dog and the background. The same algorithm may segment another image of a dog into six regions: the body of the dog, the front legs of the dog, the rear legs, the eyes, background grass and the sky.

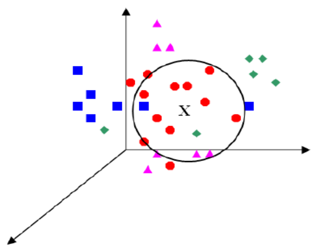


Fig.6.Feature Space by Query Image

One important aspect of any CBIR system is the distance used to compare the visual features extracted from the images. Such a distance affects directly the time spent to processing a visual query and the quality of the retrieval effectiveness. The better the distance simulates the human perception of similarity using the available visual features, the more effective is the CBIR system in retrieving relevant images to the user's need[3,7]. The computational complexity of the distance is another important issue when processing a visual query. Depending on the distance complexity, has given in equation 3, the time to compute the distance between images must be superior to the time to access the disk pages where the visual features are stored. Let h and g represent two color histograms. The Euclidean distance between the color histograms h and g can be computed as:

$$d^2(h,g)^n = \sum_{k=a,b,c}^{n} \binom{n}{k} h^k g^{n-k} \quad \dots\dots\dots\dots(3)$$

Unfortunately, from equation 3 we get the regional CBIR approaches cannot be adequately modeled in a vectorial space, because the number of regions of two images may be different and the obtained regions may also have different sizes. Based on persuasion and similarity measure by weighted Euclidean distance retrieved images and query image in the feature space. We consider 3-dimensional feature space, shown in figure.6, for these features. In his Figure, query image has represented by symbol x and database images of different classes are shown by symbols●,◆,▲, and■. Drawn circle on the feature space in Figure.6 determines search space of the query image x. Retrieved images are consisting of positive images (8 images with symbol ●) and negative images (one image with symbol■) , one image with symbol◆, and two images with symbol▲ ) that shown in the feature space. In the proposed RF, the close images to query image have more effect in the similarity measure[17].

In metric spaces, there are no restrictions about the representation of visual features. A distance d is considered a metric if, for any (images) X, Y and Z, the following properties hold:

Positiveness or Minimality: d(X, Y) >= 0

Symmetry: d(X, Y) = d(Y, X)
Reflexivity or Self-similarity: d(X, X) = 0
Triangular Inequality: d(X, Z) <= d(X, Y) + d(Y, Z)
Metric spaces can be efficiently indexed using metric access methods (MAMs). These methods make extensive use of triangular inequality property to reduce the search space and also the number of distance computations at query time.

## 6. CONCLUSION

The navigation patterns derived from the users' long term browsing behaviors are used as a good support for minimizing the number of user feedbacks. On the other hand, the proposed algorithm NPRFSearch performs the navigation-pattern-based search to match the user's intention by merging three query refinement strategies. As a result, traditional problems such as visual diversity and exploration convergence are solved. For navigation-pattern-based search, the hierarchical BFS-based KNN is employed to narrow the gap between visual features and human concepts effectively with in a very short term of relevance.

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