# KDEH Based Image Retrieval Using Invariant Features

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**ABSTRACT**

Image Retrieval scheme represents images on the basis of histograms derived from photometric color features. The main objective of this research is to apply Kernel Density Estimation function on Histogram (KDEH), to retrieve images from large collection of image database by characterizing the contents. The retrieval process is performed based on the content of images, and more precisely on a low - level visual features based method such as color and shape. In this approach, the system extracts the color features in two color spaces namely RGB and HSV. The similarity measure between two color histograms are computed by Histogram Intersection Distance (HID) and their retrieval performances are compared based on precision and recall techniques. Various edge detection methods like gradient-based edge detection and signature-based edge detection for shape feature have been proposed to detect the arbitrary objects in an image. Finally, the KDEH method is compared with a Traditional Histogram (TH) approach by varying the histogram bins with for different testing and training samples. It has been experimented that extracting the KDEH based color feature histogram provides improved results in terms of retrieval accuracy for the kind of images, which are enriched with color characteristics and the shape features perform well for the images with structural characteristics.

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## 1. INTRODUCTION

With the advent of large image database with complex images, efficient content based retrieval of images has become an important issue in today's environment. The so called Content Based Image Retrieval (CBIR) can be defined as a set of techniques for retrieving semantically relevant images from an image database based on automatically derived image features.

Main tasks of CBIR systems are to perform similarity comparison, extracting feature signatures of every image based on its pixel values and defining rules for comparing images. These features become the image representation for measuring similarity with other images in the database. Normally images are compared by calculating the difference of its feature components to other image descriptors.

Initially CBIR methods were used for global feature extraction to obtain the image descriptors. Since its inception, CBIR has been applied to numerous applications of which avoids the expense and limitations of text based searches. CBIR automatically extracts visual attributes such as color and shape invariant features for indexing and retrieving images. In CBIR systems, histograms are often used to represent the distributions of color attributes in images. One of the key issues with

CBIR is to extract useful information from the raw data to reflect the image content. Studies on users' requirements for image from image collections reveal that primitive features such as color, texture, shape or the combination of them are very useful for image description and retrieval. These features are both objective and directly derivable from the images themselves, without the need to refer to any external knowledge base [1].

## 2. Literature Review

Existing color-based general-purpose image retrieval systems roughly fall into three categories depending on the signature extraction approach used: histogram, color layout, and region-based search. Histogram search characterizes an image by its color distribution, or histogram. Many histogram distances have been used to define the similarity of two color histogram representations. Euclidean distance and its variations are the most commonly used.

In addition to texture and color, shape is one of the most essential visual features in image retrieval. For humans and animals, shape is a dominant characteristic for the identification of similar objects. Shape descriptors can be divided into two categories: region-based and contour-based method. Region–based methods [13] use the whole area of an object for shape description, while contour-based methods use only the information present in the contour of an object and the main advantages are that they Captures the shape very well, Robust to the noise, scale, and orientation and it is fast and compact.

A limitation with the current state of the art CBIR systems is that they are mainly restricted to the lowest level of query based on primitive image features such as colour and texture whereas ideally they should operate based on the semantic content (e.g. find pictures of steam trains in the country) [3]. An obvious approach to include shape is to segment the image into regions. It is then straightforward to measure region shape as well as determining spatial interrelationships between regions. The difficulty is that segmentation is inherently such a difficult task that the performance of current algorithms falls far short of being able to provide an adequate input to such schemes [2]. Rather than perform region segmentation some researchers have investigated the use of interest points as a means of localising processing to significant image windows [5]. Still, the difficulty is that corner detection and other interest operators are typically unreliable. This suggests edge detection as a more reliable approach, since it lies somewhere in between regions and points. It does not require a complete partitioning of the image like region segmentation. Only the edges are of interest, and they only cover a fraction (e.g. a tenth) of the image. Our goal is to incorporate some aspects of shape information into the CBIR process, preferably without explicitly having to extract shapes (i.e. regions) from the image. In the same vein of obtaining some aspect of shape from edges are approaches by Jain and Vailaya [4] and Zhou and Huang [6]. The former histograms are the edge orientations.

In this paper the shape of the objects is well represented by computing the statistics of the edges in an image. Hence histogram based shape features are computed on the edge pixel attributes such gradient, signature based on radius and orientation of the border pixel. The limitations of the ordinary histogram approach are that it is trying to assign the membership of a pixel in to selected nearest bins, which yields the quantized value of its membership. Hence an improved method of computing the histogram is proposed on color and shape features by applying the kernel density function.

## 3. Research Methodology: Kernel Density Estimation

Color histogram is the reduction of number of colors representing the content of an image. Color histograms [8] are widely used in image retrieval and two choices have to be made when constructing a histogram i.e. Bin width parameter and position of bin edges. The main advantage of histogram is fast to compute, invariant to rotation, translation, scaling and occlusions, easy to compute etc. Kernel Density Estimation method [9] is one of the more intuitive and widely used method for non-parametric density estimation which mainly depends on data points to reach an estimate. To remove the dependence on the end points of the bins, Kernel estimators center a kernel function at each data point. The disadvantage of histogram provides the motivation for Kernel Density Estimation. It is proposed to construct robust color invariant histogram for the purpose of Image Retrieval. The simplest well-known non-parametric density estimator is the histogram. It is a good method to provide statistical modeling among sparse or high-dimensional data. The main advantages for these approaches are: Fast convergence rate and ease smoothness.

### 3.1 KDEH Based Color Image Retrieval

Color indexing is a process by which the images and videos in the database are retrieved on the basis of their color content [7]. There are two general notions of color content: one corresponding to global color distribution, and the other corresponding to regional color information. Indexing images by global color distribution has been achieved by using KDEH based color histograms. This provides a good approach for retrieving images that have similar overall color content. A simple Architecture for KDEH Based Color Image search is shown in Figure 1.

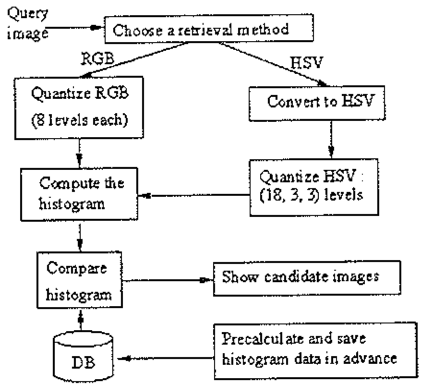


Figure.1 Flow of KDEH Based Color Image Search

In Figure 1, once a query image and retrieval methods are chosen by users, the rest of whose process is done automatically. However, the histogram data for all images in database are computed and saved in DB (Database) in advance so that only the image indexes and histogram data can be used to compare the query image with images in DB for the purpose of conducting experiment. The KDEH based retrievals used in this experiment are all based on histogram distance measures introduced in equation (11). The histogram corresponding to the query image is compared with histogram of all the images stored in the database by Histogram Intersection Distance (HID). The Histogram Intersection distance measure is used in RGB color space and in HSV color space separately, and the top 'N' images are retrieved. However, each color space requires different processing to the query image and images in Data Base.

To apply variable kernel density estimation in a principled way, two-color models like RGB, HSV are proposed through color invariant variables. As a result, the associated uncertainty is obtained for each color invariant value. The associated uncertainty is used to derive the parameterization of the variable kernel for the purpose of robust histogram construction. Let R, G, B be the red, blue component of an image, then the normalized color rg-values can be calculated as:

$$r = \frac{R}{(R+G+B)} \quad (1)$$

$$g = \frac{G}{(R+G+B)} \quad (2)$$

For the normally distributed random quantities, the standard way to calculate the standard deviations R, G and B is to compute the mean and variance estimates derived from homogeneously colored surface patches in an image under controlled imaging conditions. For the uncertainty of the normalized coordinates, r, g, b is of

$$Sr = \sqrt{\frac{R^2(\sigma B^2 + \sigma G^2) + (G+B)^2 * \sigma R^2}{(R+G+B)^4}} \quad (3)$$

$$Sg = \sqrt{\frac{G^2(\sigma B^2 + \sigma R^2) + (R+B)^2 * \sigma G^2}{(R+G+B)^4}} \quad (4)$$

$$S\theta = \sqrt{\left(\frac{3}{4}\right) * \left(\frac{(B-G)^2 * \sigma R^2 + (B-R)^2 * \sigma G^2 + (R-G)^2 * \sigma B^2}{(R^2+G^2+B^2-R*G-R*B-B*G)^2}\right)} \quad (5)$$

From the analytical study of Eqn. (3) and (4), it can be derived that normalized color becomes unstable around the black point R= G= B= 0.

A density function f gives a description of the distribution of the measured data. A well-known density estimator is the histogram. The (one-dimensional) histogram is defined as:

$$f(x) = \left(\frac{\text{Number of } X_i \text{ in the same bin as x}}{(n*h)}\right) \quad (6)$$

Where n is the number of pixels with value $X_i$ in the image, h is the bin width, and x is the range of the data. Two choices have to be made when constructing a histogram. First, the bin-width parameter needs to be chosen. Second, the position of the bin edges needs to be established. Both choices affect the resulting estimation. Alternatively, Kernel estimators smooth out the contribution of each observed data point over a local neighborhood of that data point. The contribution of data point x(i) to the estimate at some point x depends on how apart x(i) and x are. The extent of this contribution is dependent upon the shape of the kernel function adopted and the width accorded to it. The kernel density estimator whose bandwidth is h, then the estimated density at any point x is:

$$f(x) = \left(\frac{1}{n*h}\right) * \left(\sum_{i=1}^{n} K\left(\frac{x-X_i}{h}\right)\right) \quad (7)$$

Here, kernel K is a function satisfying $\int K(x)dx = 1$, ensures that the estimates f(x) integrates to 1 and where the kernel function K is usually chosen to be a smooth unimodal function with a peak at zero. In the variable kernel density estimator, the single h is replaced by n and values should be non-negative and continuous. Assuming normally distributed noise, the distribution is approximated well by the Gauss distribution.

$$K(x) = \left(\frac{1}{\sqrt{2\Pi}}\right) * \exp^{-\left(\frac{x^2}{2}\right)} \quad (8)$$

The variable Kernel method for the bivariate, normalized RGB Kernel is given by:

$$F(r,g) = \left(\frac{1}{n}\right) * \left(\sum_{i=1}^{n} \left(\frac{1}{sr}\right) * K\left(\frac{r-r_i}{sr_i}\right) * \left(\frac{1}{sg}\right) * K\left(\frac{g-g_i}{sg_i}\right)\right) \quad (9)$$

Where r, g are derived from (3) equation (1) and equation (2). The variable Kernel method estimating the univariate, directional hue density is given by:

$$f(\theta) = \left(\frac{1}{n}\right) * \left(\sum_{i=1}^{n} \left(\frac{1}{S\theta}\right) * K\left(\frac{\theta-\theta_i}{S\theta_i}\right)\right) \quad (10)$$

### 3.1.1 Color Based Histogram Discrimination

Histogram Intersection distance measure is used for measuring the similarity of two color histograms. In general, the techniques for comparing probability distributions, such as the kolmogoroff-smirnov test are not appropriate for color histograms. This is because visual perception determines similarity rather than closeness of the probability distributions. Essentially, the color distance formulas [10] arrive at a measure of similarity between images based on the perception of color content. Let h and g represent two color histograms. The intersection of histograms h and g is given by:

$$d(h,g)=\frac{\sum_{A}\sum_{B}\sum_{C}\min(h(a,b,c),g(a,b,c))}{\min(|h|,|g|)} \qquad (11)$$

Where |h| and |g| gives the magnitude of each histogram, which is equal to the number of samples. Colors not present in the user's query image do not contribute to the intersection distance. This reduces the contribution of background colors. The sum is normalized by the histogram with fewest samples.

### 3.1.2 Retrieval Effectiveness

Two metrics for retrieval effectiveness are recall and precision. Recall signifies the relevant images in the database that are retrieved in response to a query. Precision is the proportion of the retrieved images that are relevant to the query. Let A be the set of relevant items, let B the set of retrieved items and a, b, c and d are given in Figure 2.

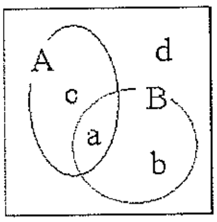


Figure 2. Sets for explaining retrieval effectiveness

In Figure 2, 'a' stands for 'retrieved relevant' images, 'b' for 'retrieved irrelevant' images, 'c' for 'unretrieved relevant' images and 'd 'for 'unretrieved irrelevant' images. Then recall and precision are defined as per the following conditional probabilities

$$recall=P\left(\frac{B}{A}\right)=\frac{P(A\cap B)}{P(A)}=\frac{a}{a+c} \qquad (12)$$

$$precision=P\left(\frac{A}{B}\right)=\frac{P(A\cap B)}{P(B)}=\frac{a}{a+b} \qquad (13)$$

With these conditions, image retrieval is said to be more effective if precision values are higher at the same recall values.

### 3.2 KDEH-shape Based Image Retrieval

The objects are segmented from an image and then indexed to database. For each object segmented, a shape region is obtained and the shape can be indexed [11] using either contour-based shape descriptor, since the shape from segmented objects is quite complex, especially the non-rigid objects. When a query image is compared with a target image in database, the objects of the query image is compared with the indexed objects in the target image. The similarity between the query image and the target image can be measured by the two most similar objects in the two images [12]. The simple architecture for KDEH based shape image search is shown in the following figure 3.

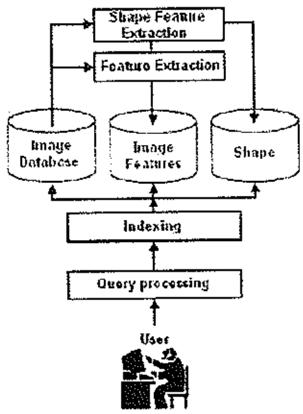


Figure 3. Flow of KDEH Based Shape Image Search

If a shape is used as feature, edge detection is the first step to extract that feature. Invariance to translation, rotation, and scale is required by a good shape representation. Sustaining deformation contour matching is an important issue at the matching process. Various edge detection methods are used to detect arbitrary edge points, which are compared with other operators to get the better performance.

### 3.2.1 Edge Based Approaches

KDEH based shape image retrieval is based on gradient-based edge detection and signature based edge detection [15]. A gradient-based approach uses some of the edge detection operators such as Sobel, Canny, Prewitt, Roberts, and Laplacian.

### 3.2.1.1 Gradient Based Edge Detection

Gradient edge detection is the second and more widely used technique. Here, the image is convolved with only two masks, one estimating the gradient in the x-direction Gx, the other the gradient in the y-direction Gy. The absolute gradient magnitude is then given by

$$|G| = \sqrt{Gx^2 + Gy^2} \qquad (14)$$

Eqn. 14. can be approximated with

$$|G| = |Gx| + |Gy| \qquad (15)$$

The magnitude and orientation of gradients in both x and y direction is applied to gradient edge detector operators such as Sobel, Prewitt, Canny, Roberts and zero Cross operators.

### 3.2.1.2 Signature Based Edge Detection

The Centroid radii model is to used to represent shapes. In this method, lengths of the shape's radii from centroid to boundary are used to represent the shape. The interval between radii is fixed and totally 8 intervals are considered. Without loss of generality, the intervals are taken clockwise, starting from the x-direction. After the object contour has been detected the first step in shape representation for an object is to locate the central point of the object. To permit invariance to translation, rotation and scaling the geometric center of the object is selected as a reference point.

The contour is characterized using a sequence of contour points described in a polar form. Here the pole at the centroid (xc, yc) is taken, then the contour graph can be represented by a polar equation $d=f(\theta)$ and each contour point (x, y) has the polar description, where x, y, d and $\theta$ are related using equation (16) and (17).

| Query Image | Histogram Intersection Distance-HSV space | | | | | |
|---|---|---|---|---|---|---|
| | TH (% of Classification) | | | KDEH (% of Classification) | | |
| | Bin 10 | Bin 20 | Bin 30 | Bin 10 | Bin 20 | Bin 30 |
| Building | 85.6 | 79.3 | 81.4 | 91.2 | 93.1 | 88.3 |
| Buses | 81.4 | 83.5 | 78.4 | 90.6 | 95.3 | 89.4 |
| Dinosaur | 89.1 | 89.2 | 90.8 | 94.9 | 98.6 | 93.6 |
| Roses | 79.2 | 74.0 | 71.0 | 90.0 | 90.5 | 82.4 |
| Horses | 81.6 | 81.4 | 82.3 | 89.1 | 89.2 | 87.5 |

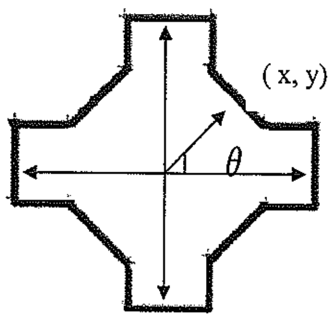


Figure 4 Distance and angle of the contour points relative to centroid.

For an arbitrary shape shown in above figure, the Centroid of an object can be determined according to the below equations.

$$D=\sqrt{(x-xc)^2+(y-yc)^2} \tag{16}$$

$$\theta=\mathrm{Tan}^{-1}\left(\frac{yc}{xc}\right) \tag{17}$$

## 4. Simulation Results

In this research, 500 images are drawn from the corel database [8] with different samples in each category of images. Experiments were conducted with varying histogram bins for both color and shape features and their performance evaluation for TH and KDEH shown in Table 2 and Table 4.

### 4.1 KDEH Based Color Image Retrieval

This section shows the results obtained by KDEH and TH based color image retrieval for two color spaces HSV and RGB.

Table 1 KDEH Based Color Image Retrieval Performance in HSV and RGB Space for the top most images for bin 5. For each query image the table also shows HSV space provides better performance when compared to RGB for the topmost images.

| Query Image | Histogram Intersection Distance for Bin 5 | | | | | |
|---|---|---|---|---|---|---|
| | Top50 Images | | Top75 Images | | Top 100 Images | |
| | *HSV* | *RGB* | *HSV* | *RGB* | *HSV* | *RGB* |
| Building | 99.4 | 92 | 98 | 87 | 91 | 85 |
| Buses | 98 | 92 | 94.6 | 89 | 90 | 87.3 |
| Dinosaur | 100 | 100 | 97 | 100 | 94 | 99.6 |
| Roses | 96.4 | 92 | 92.2 | 90 | 90 | 83.2 |
| Horses | 93.6 | 98 | 91.2 | 90 | 89 | 84 |
| **Average** | **HSV: 90.2 RGB: 87.82** | | | | | |

Table 2 KDEH and TH based Color Image Retrieval Performance evaluation in HSV Color space for bin 10, bin 20 and bin 30. For every bin, KDEH provides better classification rate when compared to TH in HSV color space.

Table 3 KDEH and TH based Color Image Retrieval Performance evaluation in RGB color space for bin 10, bin 20 and bin 30. For every bin, KDEH provides better classification rate when compared to TH in RGB color space.

| Query Image | Histogram Intersection Distance-RGB space | | | | | |
|---|---|---|---|---|---|---|
| | TH (% of Classification) | | | KDEH (% of Classification) | | |
| | Bin 10 | Bin 20 | Bin 30 | Bin 10 | Bin 20 | Bin 30 |
| Building | 81.6 | 78.4 | 81.9 | 85.8 | 85.8 | 89.6 |
| Buses | 81.4 | 83.6 | 82.0 | 87.3 | 87.3 | 85.3 |
| Dinosaur | 89.1 | 89.1 | 90.1 | 99.6 | 99.6 | 97.1 |
| Roses | 79.2 | 82.4 | 82.6 | 83.2 | 83.2 | 89.3 |
| Horses | 81.6 | 79.6 | 77.7 | 84.3 | 84.8 | 82.6 |

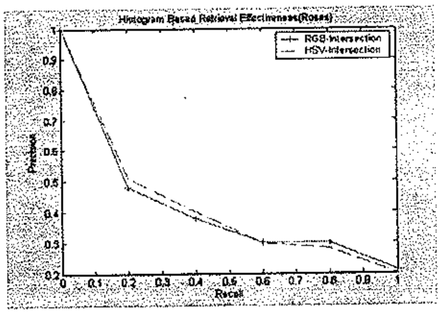


Figure 5 Comparison Graph representing the KDEH based color image retrieval effectiveness over HSV and RGB space based on recall and precision for roses category. As the recall rate increases precision rate decreases for the first topmost images.

### 4.2 KDEH Based Shape Image Retrieval

In this research 360 images are taken from the COIL-20 database with different samples in each category of images. Table 4 shows the TH and KDEH based Shape Image Retrieval over various edge-detected operators like Sobel, Canny, Prewitt, Roberts and Zero Crossing for various bins like bin10, bin20 and bin30.

Table 4 TH and KDEH based Shape Image Retrieval over various edge-detected operators. The table shows KDEH provides better classification rate for every bin compared to TH Also in KDEH, Roberts's operator shows the higher performance when compared to other operators.

| Edge detect operators | TH (% of Classification) | | | KDEH (% of Classification) | | |
|---|---|---|---|---|---|---|
| | Bin 10 | Bin 20 | Bin 30 | Bin 10 | Bin 20 | Bin 30 |
| Sobel | 74.43 | 63.6 | 60.57 | 81.97 | 78.4 | 73 |
| Canny | 77.85 | 74.3 | 72.58 | 81.41 | 83.6 | 85 |
| Prewitt | 74.36 | 68.7 | 56.33 | 80.14 | 71.9 | 68 |
| Roberts | 71.83 | 56.9 | 58.24 | 82.25 | 81.7 | 83 |
| laplacian | 72.56 | 59.2 | 60.65 | 78.03 | 79.3 | 81 |
| Zero crossing | 72.56 | 69.2 | 60.65 | 78.02 | 81.5 | 80 |

## 5. Future Work

Main focus of this research work is to retrieve the images based on two low level features namely color and shape by using KDEH based approach. In future, it is possible to use the histogram intersection distance measure with combined shape and color feature preferably with texture features to improve the overall image retrieval performance. The invariant features can also be obtained by combining both the color and the shape features of image.

## 6. Conclusion

In this paper, histogram-based search methods are applied in two different color spaces, namely RGB and HSV. From the analysis it has been observed that the kernel density function applied on histogram yields better result compared to the conventional histogram methods. These methods are applied in two color spaces and are exhaustively compared by providing precisions vs. recall graphs for each image class and for all test images. In general, histogram-based retrievals in HSV color space showed better performance than in RGB color space. In a viewpoint of computation time, using HSV color space is faster than using RGB color. KDEH based color and a shape feature provides better performance when compared to TH. The histogram-based image retrieval based on edge detector operators were exhaustively compared by providing working with different set of training and testing image. It has been experimented that extracting the color feature histogram provides improved results in terms of retrieval accuracy for the kind of images, which are enriched with color characteristics and the shape features perform well for the images with structural characteristics.

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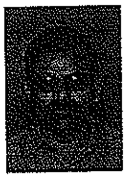

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