

# Design and Implementation of Content Based Image Retrieval on Fpga using Linear Multiple Feature Extraction Method

Sheetal Gadekar<sup>1</sup>; Rakesh Madliya<sup>2</sup>

Research Scholar<sup>1</sup>; HOD of EC Department: BM College of Technology<sup>2</sup>

E-mail: Sheetalgdkr02@gmail.com<sup>1</sup>; hod.electronics@bmcollege.ac.in<sup>2</sup>

## ABSTRACT

The paper gives idea to describe our research and solution to the problem of designing a Content Based Image Retrieval, CBIR system. It provides the problem, the proposed solution, the final solution and the accomplishments achieved. With the rapid use of the increase in image database sizes and its usefulness in various application, there occurs need of CBIR. Firstly, this paper describes the primitive features of an image; texture, colour, and shape. These features get extracted and used as the basis for a similarity check between images. The algorithms used to calculate the similarity between extracted features, are then explained.

Existing image retrieval systems suffer from a performance variance for different queries. Severe performance variance may greatly degrade the effectiveness of the subsequent query-dependent ranking optimization algorithms, especially those that utilize the information mined from the initial search results. In this paper, we tackle this problem by proposing a query difficulty guided image retrieval system, which can predict the queries' ranking performance in terms of their difficulties and adaptively apply ranking optimization approaches. We estimate the query difficulty by comprehensively exploring the information residing in the query image, the retrieval results, and the target database. To handle the high-dimensional and multi-model image features in the large-scale image retrieval setting, we propose a Linear multiple feature embedding algorithms which learn a linear transformation from a small set of data by integrating a joint subspace in which the neighborhood information is preserved. The transformation can be effectively and efficiently used to infer the subspace features of the newly observed data in the online setting. We prove the significance of query difficulty to image retrieval by applying it to guide the conduction of three retrieval refinement applications, i.e., reranking, federated search, and query suggestion.

## Keywords

CBIR , Linear Multiple Feature Extraction Method, Color Quadratic Distance Metric.

## 1. INTRODUCTION

As processors become increasingly powerful, and memories become increasingly cheaper, the deployment of large image databases for a variety of applications have now become realisable. Databases of art works, satellite and medical imagery have been attracting more and more users in various professional fields — for example, geography, medicine, architecture, advertising, design, fashion, and publishing. Effectively and efficiently accessing desired images from large and varied image databases is now a necessity.

### 1.1 Definition

CBIR or Content Based Image Retrieval is the retrieval of images based on visual features such as colour, texture and shape. Reasons for its development are that in many large image databases, traditional methods of image indexing have proven to be insufficient, laborious, and extremely time consuming. These old methods of image indexing, ranging from storing an image in the database and associating it with a keyword or number, to associating it with a categorized description, have become obsolete. This is not CBIR. In CBIR, each image that is stored in the database has its features extracted and compared to the features of the query image. It involves two steps:

*Feature Extraction:* The first step in the process is extracting image features to a distinguishable extent.

*Matching:* The second step involves matching these features to yield a result that is visually similar.

CBIR System:-

Several CBIR systems currently exist, and are being constantly developed. Examples are:

- QBIC or Query by Image Content was developed by IBM, Almaden Research Centre, to allow users to graphically pose and refine queries based on multiple visual properties such as colour, texture and shape. It supports queries based on input images, user-constructed

sketches, and selected colour and texture patterns.

- *VIR Image Engine* by Virage Inc., like QBIC, enables image retrieval based on primitive attributes such as colour, texture and structure. It examines the pixels in the image and performs an analysis process, deriving image characterization features.
- *Visual SEEK* and *Web SEEK* were developed by the Department of Electrical Engineering, Columbia University. Both these systems support colour and spatial location matching as well as texture matching.
- *NeTra* was developed by the Department of Electrical and Computer Engineering, University of California. It supports colour, shape, spatial layout and texture matching, as well as image segmentation.
- *MARS* or *Multimedia Analysis and Retrieval System* was developed by the Beckman Institute for Advanced Science and Technology, University of Illinois. It supports colour, spatial layout, texture and shape matching.
- *Viper* or *Visual Information Processing for Enhanced Retrieval* was developed at the Computer Vision Group, University of Geneva. It supports colour and texture matching.

## 2. Related Work

### *Difficulty Guided Image Retrieval Using Linear Multiple Feature Embedding*

In this paper, we propose a query difficulty estimation integrated image retrieval system. The advantages of the proposed system are two-fold. Firstly, the proposed difficulty guided system solves the problem of performance and efficiency degradations of query dependent strategies for online ranking optimizations. Essentially, the problem is introduced by the performance variance of the initial ranking. Furthermore, the proposed linear transformation LME encodes locality information from multiple features and is suitable for online image retrieval applications. The experiments conducted on three datasets have demonstrated the superiority of the QDE integrated image retrieval system, in both improving the retrieval accuracy and reducing the computational cost.

### *A Boosting Framework for Visuality-Preserving Distance Metric Learning and Its Application to Medical Image Retrieval*

In this paper, we present a novel framework that learns a distance metric from side information. Unlike the other distance metric learning algorithms that are designed to learn a full matrix for distance metric, and therefore, suffer from computational difficulty, the proposed algorithm first learns a binary representation for data and then computes the

weighted Hamming distance based on the learned representation. A boosting algorithm is presented to facilitate the learning of the binary representation and the weights that are used to form the Hamming distance. In addition to the computational efficiency, another advantage of the proposed algorithm is that it is able to preserve both the semantic relevance and the visual similarity. This is realized through the introduction of links that pair visually similar images. By training over the combination of visual pairs and pair wise constraints that are generated based on semantic relevance, the resulting distance metric is able to preserve both the visual similarity and semantically relevance. In contrast, the previous work on distance metric learning tends to focus only on the semantic relevance. We demonstrate the effectiveness of the proposed algorithm in the context of an ISADSS system for breast cancer and on two standard image data sets.

### *Content-Based Microscopic Image Retrieval System for Multi-Image Queries*

In this paper, we have presented a novel content-based microscopic image/slide retrieval algorithm. We have demonstrated that by using the proposed weighting scheme inspired by IR theory, the slide-level retrieval performance of the CBIR system is considerably better than the traditional image-level retrieval accuracy for all seven subtypes of two challenging diseases, which have inter- and intrareading semantic variations, intraslide semantic variations, and intersubtype visual similarities. In the first tier, only one slide among 44 NB slides is misclassified, and in the second tier, about 26 percentage points of improvement was achieved on the classification accuracy at the first rank retrieval over all diseases by using the proposed score weighting strategy. This CBIR system can enable the user, e.g., a pathologist, to select multiple HPF regions from a suspected tissue and submit those images as a query to the CBIR system and retrieve the most relevant slides with their semantic annotations with higher accuracies. The results, achieved under those challenging conditions, are also promising for automatic and unsupervised selected query images based on their HPF regions. Application of the proposed weighting strategy, inspired by the IR theory, is not limited to microscopic images only, and can be also useful for any type of multi query search and content-based retrieval systems.

## 2. Problem Motivation

Image databases and collections can be enormous in size, containing hundreds, thousands or even millions of images. The conventional method of image retrieval is searching for a keyword that would match

the descriptive keyword assigned to the image by a human categorizer. Currently under development, even though several systems exist, is the retrieval of images based on their content, called *Content Based Image Retrieval, CBIR*. While computationally expensive, the results are far more accurate than conventional image indexing. Hence, there exists a trade off between accuracy and computational cost. This trade off decreases as more efficient algorithms are utilized and increased computational power becomes inexpensive.

**Problem Statement**

The problem involves entering an image as a query into a software application that is designed to employ CBIR techniques in extracting visual properties, and matching them. This is done to retrieve images in the database that are visually similar to the query image.

**Proposed Solution**

The solution initially proposed was to extract the primitive features of a query image and compare them to those of database images. The image features under consideration were colour, texture and shape. Thus, using matching and comparison algorithms, the colour, texture and shape features of one image are compared and matched to the corresponding features of another image. This comparison is performed using colour, texture and shape distance metrics. In the end, these metrics are performed one after another, so as to retrieve database images that are similar to the query. The similarity between features was to be calculated using algorithms used by well known CBIR systems such as IBM’s QBIC. For each specific feature there was a specific algorithm for extraction and another for matching.

**3. Methodology**

What was accomplished was a software application that retrieved images based on the features of texture and colour, only. Colour extraction and comparison were performed using *colour histograms* and the *quadratic distance algorithm*, respectively. Texture extraction and comparison are performed using an *energy level algorithm* and the *Euclidean distance algorithm*, respectively.

**4.1. Colour**

One of the most important features that make possible the recognition of images by humans is colour. Colour is a property that depends on the reflection of light to the eye and the processing of that information in the brain. We use colour everyday to tell the difference between objects, places, and the time of day. Usually colours are defined in three dimensional colour spaces. These could either be *RGB* (Red, Green, and Blue), *HSV* (Hue, Saturation, and Value) or *HSB* (Hue, Saturation, and Brightness). The last two are dependent on the human perception of hue, saturation, and brightness.

Most image formats such as *JPEG, BMP, GIF*, use the RGB colour space to store information. The RGB colour space is defined as a unit cube with red, green, and blue axes. Thus, a vector with three co-ordinates

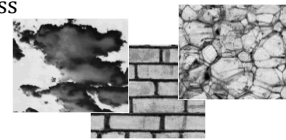
represents the colour in this space. When all three coordinates are set to zero the colour perceived is black. When all three coordinates are set to 1 the colour perceived is white. The other colour spaces operate in a similar fashion but with a different perception.

**4.2 Texture**

Texture is that innate property of all surfaces that describes visual patterns, each having properties of homogeneity. It contains important information about the structural arrangement of the surface, such as; clouds, leaves, bricks, fabric, etc. It also describes the relationship of the surface to the surrounding environment. In short, it is a feature that describes the distinctive physical composition of a surface.

Texture properties include:

- Coarseness
- Contrast
- Directionality
- Line-likeness
- Regularity
- Roughness



**Figure: Examples of Textures**

Texture is one of the most important defining features of an image. It is characterized by the spatial distribution of gray levels in a neighbourhood. In order to capture the spatial dependence of gray-level values, which contribute to the perception of texture, a two-dimensional dependence texture analysis matrix is taken into consideration. This two-dimensional matrix is obtained by decoding the image file; jpeg, bmp, etc.

**4.3. Shape**

Shape may be defined as the characteristic surface configuration of an object; an outline or contour. It permits an object to be distinguished from its surroundings by its outline. Shape representations can be generally divided into two categories:

- Boundary-based
- Region-based.



**Figure: Boundary-based & Region-based**

*Boundary-based shape representation* only uses the outer boundary of the shape. This is done by describing the considered region using its external characteristics; i.e., the pixels along the object boundary.

*Region-based shape representation* uses the entire shape region by describing the considered region

using its internal characteristics; i.e., the pixels contained in that region.

**5. Paper Details of Colour Quadratic Distance Metric**

The equation we used in deriving the distance between two colour histograms is the quadratic distance metric:

$$d^2(Q, I) = (H_Q - H_I)^t A (H_Q - H_I)$$

The equation consists of three terms. The derivation of each of these terms will be explained in the following sections. The first term consists of the difference between two colour histograms; or more precisely the difference in the number of pixels in each bin. This term is obviously a vector since it consists of one row. The number of columns in this vector is the number of bins in a histogram. The third term is the transpose of that vector. The middle term is the similarity matrix. The final result *d* represents the colour distance between two images. The closer the distance is to zero the closer the images are in colour similarity. The further the distance from zero the less similar the images are in colour similarity.

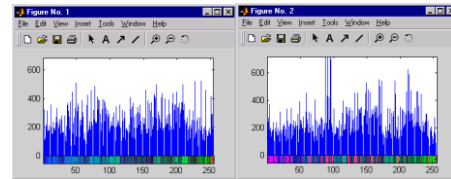
**5.1. Histograms**

We used Global colour histograms in extracting the colour features of images. In analyzing the histograms there were a few issues that had to be dealt with. First there was the issue of how much we would quantize the number of bins in a histogram. By default the number of bins represented in an image's colour histogram using the *imhist()* function in Mat Lab is 256. Meaning that in our calculations of similarity matrix and histogram difference, the processing would be computationally expensive. Initially we decided to quantize the number of bins to 20. This means that colours that are distinct yet similar are assigned to the same bin reducing the number of bins from 256 to 20. This obviously decreases the information content of images, but decreases the time in calculating the colour distance between two histograms. On the other hand keeping the number of bins at 256 gives a more accurate result in terms of colour distance. Later on we went back to 256 bins due to some inconsistencies obtained in the colour distances between images. This had nothing to do with quantizing the image but rather with the types of images we were using.

The second issue was in which colour space we would present our colour map. Should it be RGB or HSV? This was solved right away when we found that *QBIC*'s similarity matrix equation was using the HSV colour space in its calculation. There hasn't been any evidence to show which colour space generates the best retrieval results, thus the use of this colour space did not restrict us an anyway.

**5.2. Similarity Matrix**

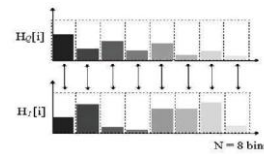
As can be seen from the colour histograms of two images *Q* and *I* in the figure below, the colour patterns observed in the colour bar are totally different. This is further confirmed when one sees the respective colour maps in the following table.



(a) Image Q (b) Image I

**Figure: Colour Histograms of two images.**

A simple distance metric involving the subtraction of the number of pixels in the 1<sup>st</sup> bin of one histogram from the 1<sup>st</sup> bin of another histogram and so on is not adequate. This metric is referred to as a *Minkowski-Form Distance Metric*, shown below, which only compares the "same bins between colour histograms".

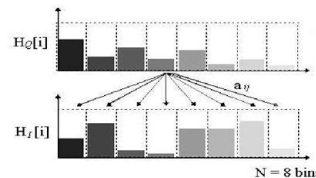


**Figure: Minkowski Distance Approach**

This is the main reason for using the quadratic distance metric. More precisely it is the middle term of the equation or similarity matrix *A* that helps us overcome the problem of different colour maps. The similarity matrix is obtained through a complex algorithm:

$$a_{q,j} = 1 - \frac{\left[ (v_q - v_j)^2 + (s_q \cos(h_q) - s_j \cos(h_j))^2 + (s_q \sin(h_q) - s_j \sin(h_j))^2 \right]^{1/2}}{\sqrt{5}}$$

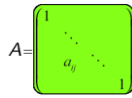
which basically compares one colour bin of *H<sub>Q</sub>* with all those of *H<sub>I</sub>* to try and find out which colour bin is the most similar, as shown below:



**Figure: Quadratic Distance Approach**

This is continued until we have compared all the colour bins of *H<sub>Q</sub>*. In doing so we get an *N x N* matrix, *N* representing the number of bins that indicates whether the colour patterns of two histograms are similar is the diagonal of the matrix, shown below. If the diagonal entirely consists of one's then the colour patterns are identical. The further the numbers in the diagonal are from one, the less similar the colour

patterns are. Thus the problem of comparing totally unrelated bins is solved.



**Figure: Similarity Matrix A, with a diagonal of ones**

### 6 .Expected Results

After obtaining all the necessary terms, similarity matrix, and colour histogram differences, for a number of images in our database, we implemented the results in the final equation, *Quadratic Distance Metric*. Surprisingly a number of inconsistencies kept appearing in terms of the colour distances between certain images. Images that were totally unrelated had colour distances smaller than those that were very similar. An example of this can be seen with the following three images: a mosque, a hockey game, and another picture of the same hockey game, as seen below.



**(a) Faceoff3 (b) faceoff4 (c) mosque  
Figure: Tested Images**

As can be seen from the following table, the results are not consistent with how the images look to the human eye.

This was done again and again with a number of images, and resulted in the same inconsistencies. What turned out to be the cause of all this, were the

type of images we were using. At first we thought the only thing that could give inconsistent results like this was comparing images of different sizes, but we had resized all the images in our database to 256x256 before testing our algorithm. The images we had in our database where all 24-bit *JPEG*s. The problem with *JPEG* images is that they are compressed and the compression algorithm seems to affect the way the histograms are derived. We found this out by converting some of the images in our database to 6-bit uncompressed bit maps. The same images that where tested in *JPEG* format were tested again as *BMP*s. That result was consistent with how the images looked to the human eye. Images that looked similar gave small colour distances compared to those that looked very different.

#### Open issues:

- Gap between low level features and high-level concepts
- Human in the loop – interactive systems
- Retrieval speed – most research prototypes can handle only a few thousand images.
- A reliable test-bed and measurement criterion.

#### Future Work:

- Handle multi-layer images
- Include human-intractable relevance retrieval feedback system.
- Eliminate bias objects but not affecting the performance.

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