Image Tagging

using visual approach

A Thesis submitted by

Sushri Sangita Biswal

111cs0121

under the guidance of

Prof. Pankaj K. Sa

Department of Computer Science and Engineering
National Institute of Technology Rourkela
Rourkela, Orissa, 769 008, India

Department of Computer Science and Engineering

National Institute of Technology ,Rourkela

Certificate

This is to certify that this is a bonafide record of the project presented by *Sushri Sangita Biswal,111cs0121* (2014-2015) in partial fulfilment of the requirements of the degree of Bachelor of Technology in Computer Science and Engineering,NIT Rourkela.

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Prof. Pankaj K. Sa
(Project Guide)

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SUSHRI SANGITA BISWAL

111CS0121

Abstract

In today's era ,with the increase in technology ,the number of digital media is increasing at a higher rate that increases the volume of databases used to store all these images.We take images from different angles,with different sensors, at different time intervals and then use the image retrieval techniques to extract all these images.In the past ,text based annotation was used with the help of keywords but this became cumbersome .So ,we used the contents of an image for this image retrieval and specially low level features.In this paper we have implementes all the color features like color histogram,color correlogram along with gabor wavelets and wavelet transformation for efficient image retrieval.

Keywords: cross-correlation,Mutual Information,Gabor filter,HSV space,Wavelets.

Contents

1 Introduction

One of the most challenging task of this century is to tag images so that it is easy to classify and locate images in the future. It has become too difficult wen we have large database of images, due to labor intensive and time consuming. A solution to this is automatic annotation of Images.Basically in image tagging, we describe the content of an Image by keywords or text piece. In recent years ,intensive research in this area has therefore been conducted and different approaches have been proposed.In my paper, I am trying to develop an automatic tagging framework that starts from medical annotation to tagging large buildings.

In the last decade, a large number of digital medical images have been produced in hospitals. Such digital medical images include X-ray, computed tomography , digital subtraction angiography (DSA), magnetic resonance imaging (MRI), ultrasound (US), nuclear medical imaging, endoscopy, scanning laser ophtalmoscopy (SLO), microscopy, and so on. These medical images are stored in large-scale image databases facilitating medical doctors, professionals, researchers, and college students to diagnose current patients and gives various important points on various diseases with valuable information for their higher studies and research. with the increasing in number of digital images we should have various image retrieval techniques that can improve the effeciency of browsing and searching of large medical image databases. Among all advanced retrieval techniques, image annotation is considered as one of the prerequisite task for image database management (Hersh, 2009). If we manually annotate images with text,then keyword-based search can be used to retrieve the images , but this manual annotation suffers from the following limitations, especially in case of massive image databases.

1. Manual annotations requires a lot of time and labor intensive . It becomes infeasible to annotate all attributes of the image manually

with the growth of number of media images. For example consider annotation of a 60-minute video that contains more than 100,000 images consuming a vast amount of time with expenses.

2. Such annotations fails to deal with subjective perceptions. When people do image annotation, they provide descriptions with their different perceptions. Furthermore,with time, the same annotators may also have different subjective perceptions .

3. It has become difficult to provide concrete information and description for many image contents. For instance, the shape of various organs in case of medical images is too complex to describe.

To address these limitations, automatic annotation of Images is quite necessary for efficient image retrieval. Automatic image annotation has become a hot topic in the fields of multimedia, information retrieval, and machine learning also.A working model of image annotation engine can depicts lots of tags for users and then increasing the number of tagged images, or relevant tags for direct image retrieval .

2 Literature Review

Image content

The contents of an image can be a full description generally written in prose (i.e. A picture is worth 1000 words), or maybe a few keywords describing spatial, temporal, and emotional aspects too.In most of the cases, accurately identifying the image content requires intervention of humans. Many pattern recognition algorithms exists , however only few are able to interpret the extracted patterns. Artificial Intelligence algorithms can learn patterns, but such flexibility of system is generally limited by its predefined knowledge

Basically these programs use tagging for organizing and user-defined searching also. Now , Several Web-based applications includes image tagging , and non-image based features too.

1. Google ImageLabeler
2. Flickr.com
3. Facebook.com
4. 23hq.com
5. Fotki.com

Automatic image annotation is one among the difficult machine learning task and a part of computer vision .Variety of objects requires different type of image descriptors, e.g. through color histograms we can identify rainbows (Hafner et al., 1995), whereas through local image descriptors we can identify insects. Similar objects looks very different across images and maybe partially visible, thus creating the necessary of large training data sets.

Recently, I have worked only on few images that includes various Image Registration steps as the preliminary steps. Here I did only point to pint correspondence Matching using NCC,Mutual Information, SIFT and Surf.I have also considered an optimatisation powells method for NCC and Mutual Information.Then I carried out SIFT and SURF techniques for images sensed from different angles. And afterwards Images are retrieved based on content where a query Image is given and I have to retrieve images from the database that looks similar.

3 Image Registration

This is the process of registeration the images in order to get maximum information about any images. It is basically used during Image Fusion,Image Mosaic etc. It is similar the way we register ourselves with a user id and password and then the way it is stored in the database.

3.1 Steps involved in Image Registration

Image registration generally consists of following steps , according to, Zitova and Flusser -

1. *M*atching of features:

   Establishment of the corresponding points between the reference and Sensed image features .

2. *E*stimation of Transform model:

   Estimation of the mapping Functions types and parameters , that aligns sensed images with the reference image

3. *R*esampling of Image and Image transformation:

   The image sensed is being transformed with the mapping functions.

3.2 Matching Techniques

3.2.1 Template Matching

Template matching is the methodology of finding the location of a sub image that is often known as the template inside a given image. We have certain methods that are used in Image registration .Here, generally we match a template that maybe the part of the given image of larger in size in comparison to the template or cropped image from a big image.When we found the corresponding templates that we can use their center for detecting the corresponding points to decide the parameters of registration . Literally ,we can say that matching of templates involves comparing a given template with given image,provided windows size remains the same , then identifying window which is most similar to template.This matching involves position calculation of an image to measure similarity between the template and the given image .Then consider the minimum distortion or maximum correlation position in order to identify the template in the given image.

The measures of distortion are ::

1. Sum of Absolute Differences (SAD)
2. Sum of Squared Differences (SSD)
3. Normalized Cross Correlation (NCC)

Generally NCC is most widely used due to its better robustness.

Lets assume the image given be g, then we match it with template f .One simple method to calculate the similarity measure or mismatch measure is to find out the difference between f and g ,the maximum absolute value gives the similarity measure.

3.2.2 SSD/SAD method

Similarity measure is given by maximum value of absolute difference. Here f is small compared to image g. Here we find out the difference and square between template f and g over the given region A and then find out the sum, this in analog form we can write as :

$$\int_A \int_A (f-g)^2 \tag{1}$$

Similarly in digital form ,

$$\sum \sum_{i,j \in A} (f(i,j) - g(i,j))^2 \tag{2}$$

when the above equation (2) is expanded :

$$\int_A \int_A (f-g)^2 = \int_A \int_A (f)^2 + \int_A \int_A (g)^2 - 2 \int_A \int_A (fg) \tag{3}$$

CAUCHY-SCHWATZ INEQUALITY

$\int\int_A (fg) \leq \sqrt{\int\int (f)^2 \int\int (g)^2}$

this is equal, g = cf, with constant c. And on converting this equation into digital form ,

$\sum_{i,j\in A}\sum (f(i,j) * g(i,j)) = \sqrt{\sum_{i,j\in A}\sum f(i,j)^2 \sum_{i,j\in A}\sum g(i,j)^2}$

if g(i,j) = c f(i,j),almost equal

we go for shifts along the x and y axis when the matching fails ,

$$\int_A\int f(x,y).g(x+u,y+v)dxdy \leq [\int_A\int f(x,y)^2 dxdy \int_A\int g(x+u,y+v)^2 dxdy] \tag{4}$$

Hence cross correlation fails and we go for normalised cross correlation.

According to Cauchy-Schwartz Inequality,

$$\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} (f(x,y).g(x+u,y+v))dxdy \leq C_{fg} \tag{5}$$

$$\frac{NCC = C_{fg}}{\sqrt{[\int\int_A g^2(x+u,y+v)dxdy]}} \tag{6}$$

3.2.3 NCC(Normalised Cross correaltion)

Earlier we did template matching for registering images. It was done only on gray scale images. The different template sizes are extracted from given image.

All image registration is tested with unnormalized cross correlation, showing the error prone registration of images with simple cross correlation. Extraction of the original image and the template from original image is depicted .When simple cross-correlation used , it results into the false positions or locations in image. So its concluded from the above that cross correlation never used for image registration.

Intensity Normalization

1. Imaging of a scene by different sensors ,or at different times , both the SSD and the C fg can be large for image that represents the same areain scene .
2. SO we need to NORMALIZE pixels in the windows before comparison.
3. This is done by subtraction of the mean of the intensities of images and then dividision by the standard deviation.

3.2.4 MUTUAL INFORMATION (MI)

MI is a concept taken from Information theory that measures the statistical or probabilistic independence between any two random variables. It measures the amount of information one variable contains about the other .When images are geometrically aligned then we get the maximum image intensity of corresponding voxel pairs.Here no assumptions are made regarding the intensity of Images in both modalities and this requires no segmentation.This makes it a powerful criteria and can be automatically applied on a large variety of applications.

In Mutual information we use CT or CT-derieved and problem is orientation rectification, of one CT image with respect to the other by in-plane shifts or rotations.

Mutual Information Theory:

Mutual information is a quantitative measurement that measures the amount of information one variable depicts about another variable. Let us assume an alphabet that contains n symbols, a1,a2..an , of probability of occurrence p(a1), p(a2)..p(an) respectively.

Assume p(a1) = 1, means a1 received with certainty; this is the case of the binary noiseless channel of communication . Any transmission type, 0 or 1, is received error free.

There is more information when a symbol occurs with a low probability . This is binary channel case ,assume, 0 is sent and 1 is received Therefore, information is inversely proportional to occurance probability .

The information that is obtained from two independent channels is the sum of the information obtained from each channel distinctly . Here the two independent channels probabilities multiplied in altogether to get the probability of the mixed event,Hence we can say that the amount of information as

$$I(a_i) = log\frac{1}{p(a_i)} \tag{7}$$

Hence we can say that, Information is inversely proportional to probability. And the channels with the least probability of occurrance will provides the most information.

$I(a_1) + I(a_2) = log\frac{1}{p(a_1)p(a_2)} = I(a_1, a_2)$

The probabilities of both the events are given ,then occurance probability of both is a product . This product gives the amount of information as a sum.

Entropy measures the amount of uncertainty,or information in any situation, for example, the message reception or any results of any event. Entropy involves probability distribution .The Shannon-Wiener entropy measure H is most commonly used as a measure of information in both signal processing and image processing.

$$\sum_{i=1}^{n} p_i log p_i \tag{8}$$

3.3 SIFT Techniques

SIFT - Scale Invariant Feature Transforms

Interesting points provides feature description of object that has many features. It is used then while object is located in any image that contains other objects. Few assumptions when features extracted from them and recorded . SIFT features in an image provides any object a feature set that is not affected by many controversies that occured in all other methods, like in object scaling and rotation.

To extract these large collection of local feature vectors and features ,SIFT algorithm applies filtering approach that comprises of 4 stages :

3.3.1 Scale-Space Extrema Detection

This filtering stage attempts to identify those scales and locations that are identifiable from different views of the same object. It is being acheived by a gaussian function.The scale space is defined by: $L(x, y,) = G(x, y,) * I(x, y)$

here , convolution is done , and G is the gaussian function with I as the input image In scale-space, twe need to stable the keypoint locations. It uses Gaussian function andalso Difference of Gaussians . D(x, y,) is given by: $D(x, y,) = L(x, y, k) - L(x, y,)$

And then that point becomes the extrema if it is the minima and maxima of all these points.

3.3.2 Keypoint Localistaion

Once the local extrema is detected it becomes suitable for keypoints.So in this step it eliminates keypoints having too low contrast on an edge.And here Laplacian value is computed for each keypoint that is generated at the step 1.

3.3.3 Orientation Assignment

Based on local image properties ,a consistent orientation is assigned to keypoints. The keypoint descriptor relative to this orientation is rotation invariant. The steps taken to find an orientation is:

1. keypoints scale are used to select the Gaussian smoothed image L
2. Gradient magnitude, m is computed
3. The orientation, is computed.
4. An histogram is formed from the gradient orientations of all the sample points.
5. The highest peak are located in the obtained histogram and then this peak is used .
6. Few keypoints are assigned with multiple orientations.
7. A parabola is fitted to the 3 histograms values that are closest to each of the peak to interpolate with the peaks position

3.3.4 Keypoint Descriptors

The local gradient data, above, is now used to generate the keypoint descriptors. The gradient information is rotated in order to line up with the keypoint orientation and then weighted by a Gaussian of variance 1.5 * keypoint scale. Further this data is then used to create a set of histograms centred around the keypoint over a window. Keypoint descriptors uses 16 histograms sets , aligned in a 4x4 boxes, each with 8 orientation bins, one for main compass directions and one for the mid-points of these directions and this results in a feature vector that contains 128 elements.

3.4 SURF Method

Earlier we have found that how we can use SIFT for detection and description of keypoints. But the main problem is that it is comparatively slow and we need some more speeded-up version. SURF is a speeded-up version of SIFT.

Laplacian of Gaussian with Difference of Gaussian for finding scale-space used in SIFT . But in case of SURF we approximates LoG with Box Filter.

SURF uses wavelet responses in horizontal and vertical direction for orientation assignment, for a neighbourhood of size 6s. Then guassian weights are also applied to it and are plotted in a space as given in below image. For most of the applications, rotation invariance is not required at all, so we don't find this orientation, that speeds up the process. SURF improves the speed and robustness and has a U-SURF functionality.

A neighbourhood of size 20sX20s is taken around the keypoint with s as the size. It is then divided into 4x4 subregions. And for each subregion, we take both horizontal and vertical wavelet responses and forms a vector like this , $v = (\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|)$. This when represented gives SURF feature descriptor with all total of 64 dimensions. Low dimension, high speed of computation and matching, and provide better distinct features.

Here are the steps :

1. Compute the gray-scale
2. calculate the SURF features from the model image
3. Turn on camera, get the real-time input image. Convert each frame to gray-scale.
4. Compute the SURF features of the gray-scale frame.
5. Now compare between model image and input image . Determine if they represent the same point (calculation of their distance and

thresholding) ;

6. Once on obtaining the associated points pairs , the homography matching all these pairs are determined (using RANSAC or least median squares algorithm) ;
7. Using this homography drawing of the projection of the input frame in the model frame .

3.5 Template Matching Results

When we undergo template matching we observe various drawbacks .Some of the drawbacks are stated below:

1. Only applicable for almost same resolution Images.
2. It can be performed only when the template is the cropped part of the original Image.
3. Fails for Images taken at different angles.

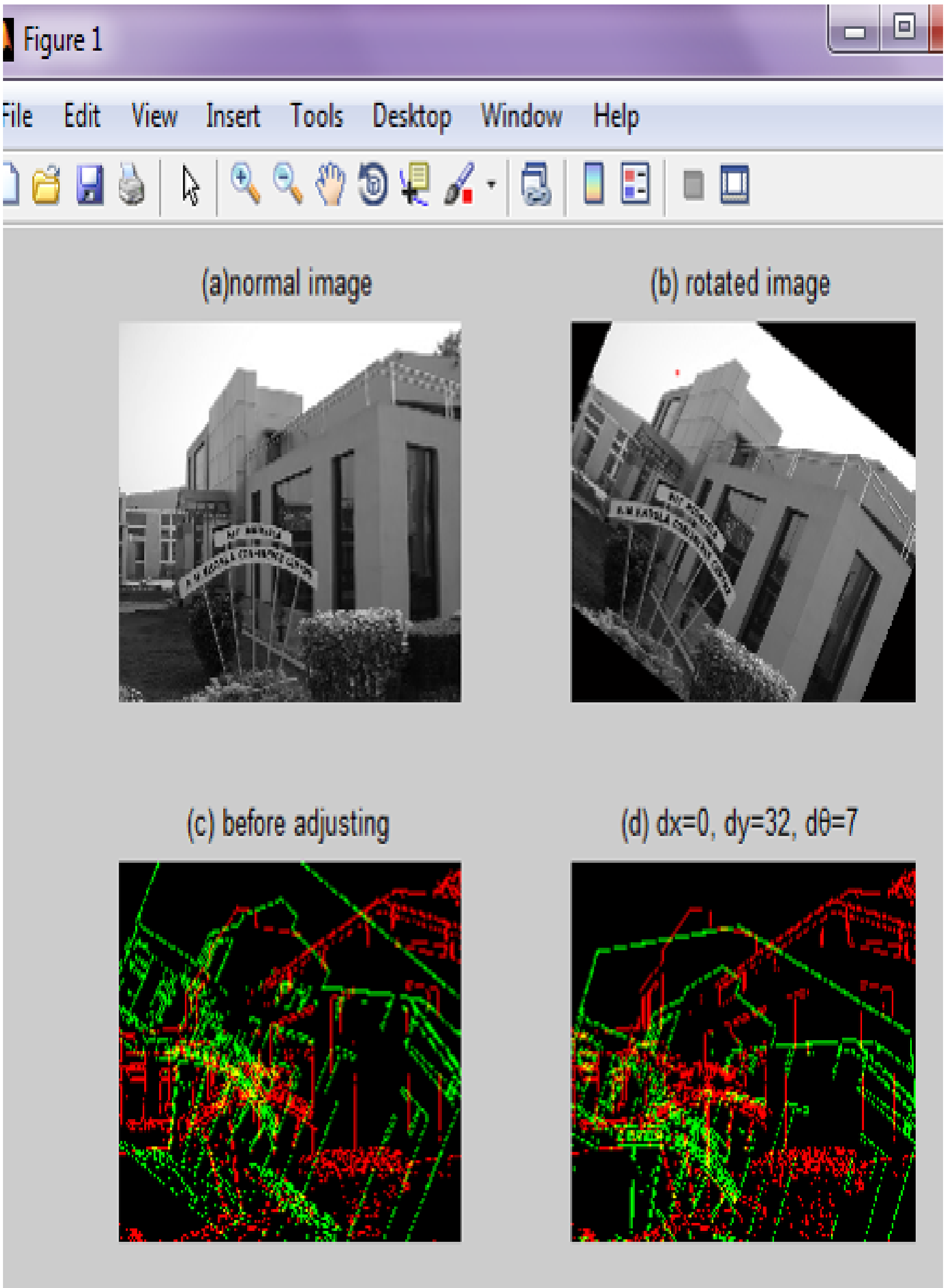


Figure 1: Mutual Information

3.6 SIFT/SURF

I've tried SIFT and SURF, found that they are not so robust, since for 2 images (one is rotated and affined a little), they don't match the features , among almost 100 feature points, only 10 matches are good.

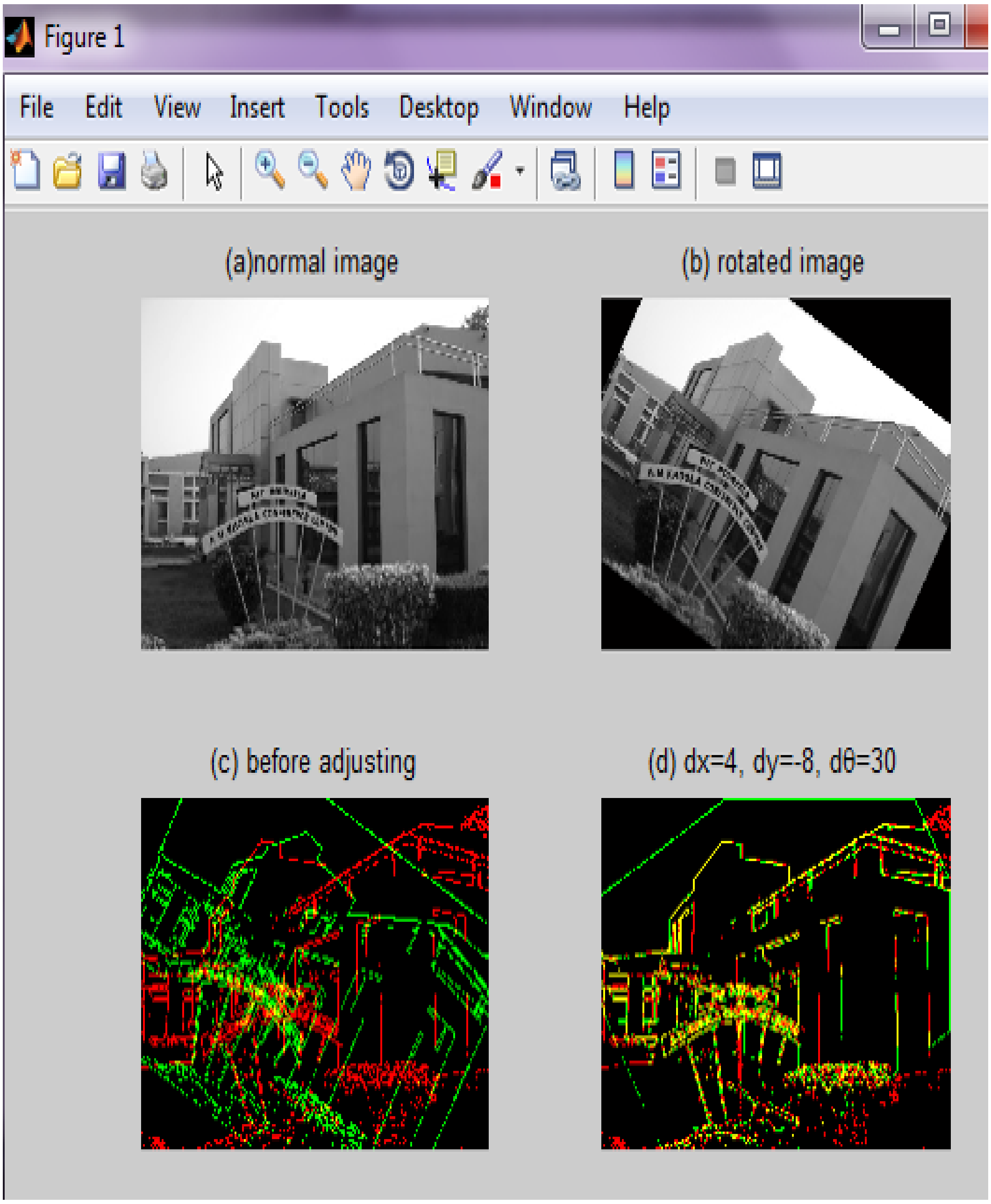


Figure 2: Gradient Mutual Information

4 Content Based Image Retrieval

4.1 WHY

In early days all Image retrieval techniques were done using text based approach that is textual annotation of Images.In Textual annotation images were first annoatted with text and then searched from the traditional database using a text based approach.In case of text approach Images are categorised by topical or semantic hierarchies that helps in easy navigations along with browsing based on standard boolean queries.But automatically generation of descriptive texts for a wide spectrum of images is not feasible so text based image retrieval system is done manually. Image annotation is too cumbersome,context sensitive when the database is too large.So it becomes too difficult in case of text-based meyhods to support a large variety of task-dependent queries.

4.2 CBIR

CBIR is the process of retrieving images from a large database or from library of digital images based on theimages visual content . It is the process of retrieving images that have similar content of colors, shapes and textures. Images have become an inevitable part of human communication.

Color is one of the most common visual feature used in CBIR because of its simplicity in extracting color information from images.Image features includes :

1. Color
2. Shape
3. Texture

Other Features includes :

1. Semantic gap

2. Pixel Intensity

4.2.1 Color Feature

HSV color space used for the histogram matching.The HSV color space is generally prefered in order to manipulate hues and saturation that either shift colors or adjust the amount of color.HSV color model the top of the hex cone represent white color with value=1 and point at the base have V=0. H measures the complementary colors that are 180 degree opposite to one another., the angle around vertical axis with red color at 0 degree.In this cone the value of S depicts a ratio that ranges from 0 on the center line vertical axis V to 1 at the sides of the hex cone.S value ranging between 0 and 1 may have V=0. When S=0,V=1 it is white GRay have intermediate values for S=0. H value is irrelevant when S=0. A pure pigment can be characterised with V=1, S=1 and color is defined by H.

4.2.2 Color Space selection and Quantisation

The color of an image is represented by popular color spaces like RGB, L*a*b*, U*V*W*, YUV and HSV . It has been found that the HSV color space generally gives the best color histogram feature, among all the different color spaces . In the content-based image retrieval generally HSV color space is used . HSV color space has three components: Hue (H), Saturation (S) and Value (V) .It is based on the cylinder coordinates.

Color quantization reduces the use of distinct colors in an image without affecting any of the visual properties of an image.It is a lossy compression technique that compresses a large umber of values to a single value.On reducing the number of colors required to represent the digital images reduces its file size.On combining color quantization with dithering in order to create an impression of a larger variety of colors and thus eliminating banding artifacts. A true color image consists of $2^24 = 16777216$ distinct colors hence the extraction of color feature from the true color increases complexity. So with an aim to reduce this,we use the color quantization to represent the image, without reducing in image quality.It reduces storage space and increases the speed while processing. Color quantisation effects have been noticed by many authors in image retrieval.

4.2.3 Color Histogram

A color histogram generally represents the colors distribution in an image, through a set of bins.Each histogram bin corresponds to a color in the quantized color space.This represents the number of pixels that have colors in each of color ranges, that span along the image's color space,with the set of all possible colors. A color histogram for a given image is basically represented by vector: H = H[0], H[1] H[2], H[3], H[i], , H[n]

where i is the color bin in the color histogram ,

H[i] = number of pixels of color i in the image,

n =total number of bins used in color histogram. Each pixel in an image is assigned to a bin of the color histogram. Accordingly ,i the value of each bin gives thetotal number of pixels that has the same corresponding color .So to compare images of different sizes, color histograms needs to be normalized.

4.2.4 Histogram similarity measures

An image is represented by a color histogram, that is defined by a color quantization scheme normally applied to a color model. To express the similarity between two histograms in a digital media , a metric distance is employed here. A wide variety of distance measures between histograms can be found , and is used commonly so which we have therefore used are the following.

4.2.5 Proposed Work

Here We choose to use an iterative method of Powell, that search for each iteration alternately and the maximum on its own dimension for each degree of freedom. So at the first iteration, we need to find the best translation in x, and then from this , we search the best translation in y , then using these above two translations updates , we search for the best rotations . Then we start updating the loop ,for each degree of freedom,we search the values for the next degree of freedom.

Degree of freedom is executed by dichotomy and is determined if only the central value is higher than the core values of the lower and upper intervals surrounding this central value. If the central value is higher, means tightens the search bounds around the central point, else the terminals around the center of interval-that had the highest central value is tightened too until the terminals are tightened around the final value for each degree of freedom. The global optimum search of the correlation function, or criterion of least squares by the Powell method does not guarantee convergence to the desired solution. These functions are not being convex, optimizes the likelihood successively on each dimension till convergence, so ,this method can lead to a local maximum.

Thus the proposed nethod for Color based Image retrieval demonstrates clearly that our spatial information encoding in the color index from image significantly increases the disciminating power compared to the color moment + Gabor texture features indexing techniques .

4.3 Algorithm For Proposed Scheme

1. Step 1: Load database in the Matlab .

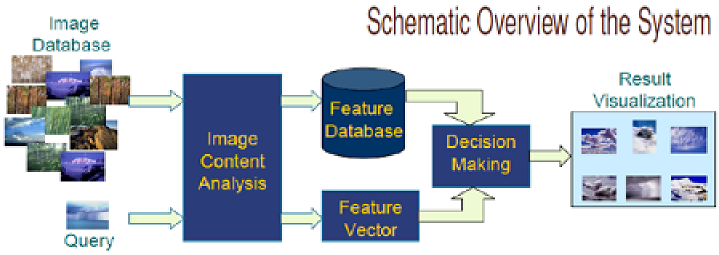


Figure 3: Steps for retrieving images

2. Step 2: The image is resized for [256. 256].
3. Step 3: Image is then from RGB to HSV.
4. Step 4: The generation of histogram of hue, saturation and value.
5. Step 5: Number of signatures n for hue, m for saturation and x for value are generated.
6. Step6:The signature of database images are stored into the mat file.
7. Step 7: The Query image is loaded.
8. Step 8: The procedure 2-7 is applied repeatedly to find signature of Query image.
9. Step 9: The normalized Intersection distance of signature of Query image is determined with stored signature of database.
10. Step 10: The normalized Intersection distance values are sorted to perform indexing.
11. Step 11: The result are displayed on GUI.
12. Step 12: The folder is createdin the name of corresponding variants.
13. Step 13: The procedure 2-13 is applied for various Hue, Saturation and Value steps.

4.4 Performance measure

To evaluate the performance of a CBIR system, two measures, namely, the recall and the precision [9], were borrowed from traditional information retrieval. Let A be the set of images in the base which are appropriate to the image request q, and B the set of returned images as result for that query. A representative diagram to explain performance measures of retrieval .

Precision=Ration between number of relevant images retrieved to total num of Images retrieved.

4.5 Experimentation

4.5.1 Image database

The used base of images comprises 500 color images. It was downloaded from http://wang1.ist.psu.edu/. The original image database comprises 1000 images divided into 10 classes. We chose the use of 500 images and 5 classes for calculation reasons. Each class represents a definite topic: African and villages, beach, buildings, bus and dinosaurs.

4.5.2 Developed prototype

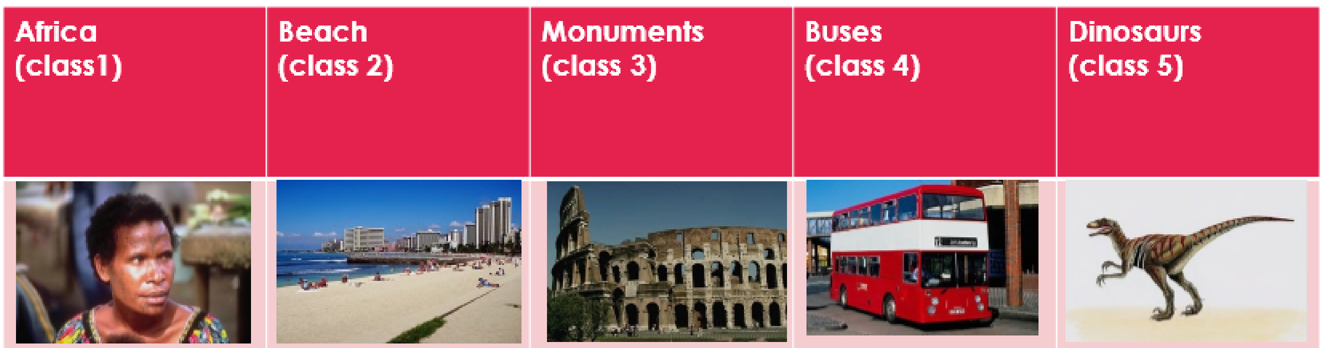


Figure 4: Dataset

Our prototype has been developed for the purpose of studying the impact of color quantization on the accuracy (precision) of CBIR. Precision represents in a retrieval process the chance of obtaining images which are similar to the image request among a group of n returned images. In our case we have calculated the precision of the top 25 of returned images. This number is approximately the number of the first returned images by a retrieval system as thumbnails. As described above, the first step consists of loading images from the image base. In the second step, color histograms are calculated according to a quantization scheme (i, i, i) such as i max-quantization. The third step consists of performing a search for 10 (15, 20) images. We have to note that those images have been randomly chosen from the base but with one condition; the different classes must participate by the same number of images (if we take 5 images from the first class, we have to take 5 from the second class and the third and so on). If max-quantization is reached the process stops and graph y= f(x) is displayed such as: x is the quantization scheme, y is obtained precision.

5 Conclusion and Results

We have purposefully kept only 7 relevant images of the particular query image type in the adatbase folder along with other irrelevant images.We have designed a 3*3 matrix for showing the resultant retrieved images in the result window.Out of the toatl 10 images in the resultant matrix only 7 relevant images are selected based on the nearest Intersection distance. Hence the combination of different Hue,Saturation, and Value steps which achieved retrieving all the 7 relevant images from the database folder in the least time is the best possible combination for image retrieval in HSV color space.

Color mainly represented by color histogram,color coherence vector,color correlogram,color moment in a particular color space here HSV space.In case of Texture it is represented by Gabor transforamation on the whole image.Shape can be depicted by moment variants,major axis orientation and random transform.

CBIR provides an efficient method and automatic solution for efficient searching of images,and mostly we consider the low level features.

It retrieves the images efficiently and then we integrate it with the user interface making user friendly and meeting the customer requirements.

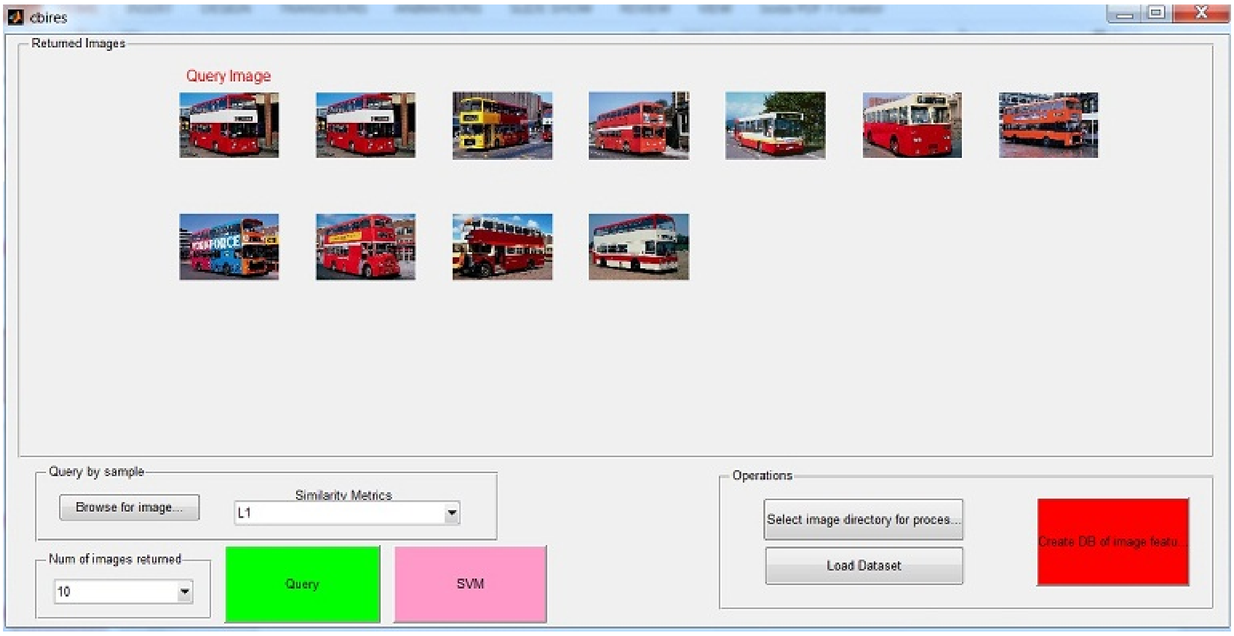
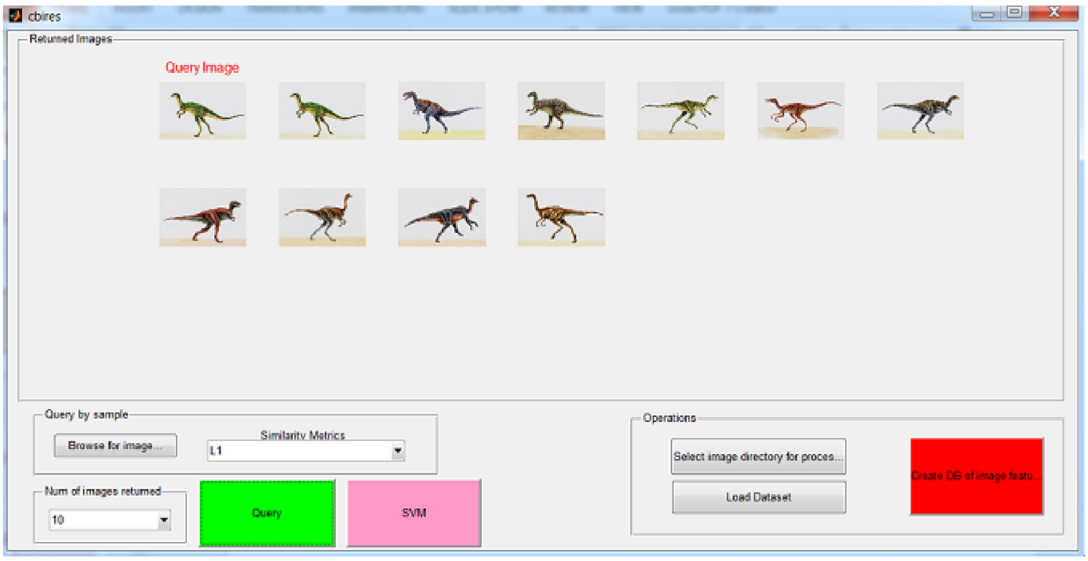


Figure 5: Bus Retrieval



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