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A Comparative Study of Sift and PCA for Content Based Image Retrieval

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ABSTRACT:

This paper presents a comparative approach for Content Based Image Retrieval (CBIR) using Scale Invariant Feature Transform (SIFT) algorithm and Principal Component Analysis (PCA) for color images. The motivation to use SIFT algorithm for CBIR is due to the fact that SIFT is invariant to scale, rotation and translation as well as partially invariant to affine distortion and illumination changes. Inspired by these facts, the paper investigates the fundamental properties of SIFT for robust CBIR by using binary MPEG-7 and Grayscale COIL-20 and Color image databases. Our approach uses detected key points and its descriptors to match between the query image and images from the database. Our experimental results show that the proposed CBIR using SIFT algorithm produces excellent retrieval result for images with many corners (concaves) and edges (convex) as compared to retrieving image with less corners and edges. The paper also presents another approach for CBIR using Principal Component Analysis (PCA) for Color images. The main aim of the paper is to employ SIFT and PCA methods on the same Image databases and perform a comparative study of results between SIFT and PCA approaches using Precision and Recall tables. The study reveals that SIFT approach provides a better Image retrieval performance for binary, gray scale and color images when compared to PCA.

INTRODUCTION:

Content-based image retrieval (CBIR) is a system which retrieves visual-similar images from large image database based on automatically-derived image features, which has been a very active research area recently.

The interest points or key point descriptors are the salient image patches that contain rich local information about an image. Many algorithms have been developed for the purpose of detecting and extracting the interest points like Harris, Hessian, Scale invariant, affine-invariant, Laplacian of Gaussian (LOG) and Difference-of- Gaussians (DOG), SIFT and SURF etc.

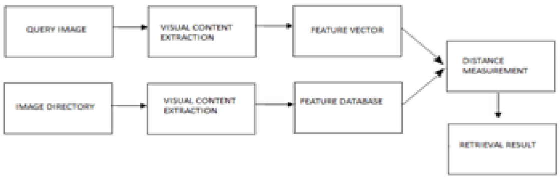

Fig 1: Block diagram of Content Based Image Retrieval.

Recently SIFT is used in many CBIR systems to describe the content of images. In the SIFT based CBIR system, a few thousand key point are extracted from each image. SIFT descriptors, which are invariant to image scaling and transformation and rotation, and partially invariant to illumination changes and affine, present the local features of an image. A typical SIFT descriptors are computed on image patches and uses 8 orientation planes. At each orientation, gradient image is sampled over a 4*4 grid, thus producing what is known as key point descriptors of feature vector containing 128 elements. For matching the key descriptors of the images a nearest neighbor search, an algorithm is used to detect similarities between key points of the two images. The SIFT algorithm can be viewed as a key point descriptor composed by four major stages. Once descriptors have been generated for more than one image, one can begin image matching [1].

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Principal Component Analysis (PCA) for Image Classification is another method for Content based Image Retrieval. The idea behind PCA is that an image can be viewed as a vector by concatenating the rows of the image one after another. If the image has square dimensions, for example, of L*L pixels then the size of the vector is L^2. PCA can perform on images to reduce dimensionality and to extract feature vector (i.e. meaningful underlying variables). Feature vector of an image describes image feature. PCA is performed by computing the eigenvectors and eigen values of the covariance matrix. The covariance is determined by the tendency to two random variables that vary together. PCA involves a mathematical procedure that transforms a number of correlated variables into a (smaller) number of uncorrelated variables called principal components [15].

METHODOLOGY:

Scale Invariant Feature Transform (SIFT) was proposed by David Lowe. The SIFT algorithm consists for four steps:

A. Scale-Space Extrema Detection:

Detection of all the possible key points of an image over all sizes and locations is the first step of SIFT. This can be achieved by implementing a difference of Gaussian (DoG) function that is invariant to scale and orientation. The scale space of an image I (x, y) is defined as a function L(x, y, σ), that is produced from the convolution of I (x, y) with a variable-scale Gaussian G(x, y, σ):

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \qquad (1)$$

Where * is the convolution operation in x and y, and G(x, y, σ) is a variable-scale Gaussian and I(x, y) is the input image.

$$G(x, y, \sigma) = \frac{1}{2TT\sigma^2} e^{-(x2+y2)/2\sigma} \qquad (2)$$

To efficiently detect stable key point locations in scale space, it uses a scale space extrema based on the difference-of-Gaussian function, D(x, y, σ), which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \qquad (3)$$

Figure 2 shows an efficient approach to construction of D(x, y, σ). To detect the local maxima and minima of D(x, y, σ) each point is compared with its 8 neighbors at the same scale, and its 9 neighbors up and down one scale. If this value is the minimum or maximum of all these points then this point is an extrema.

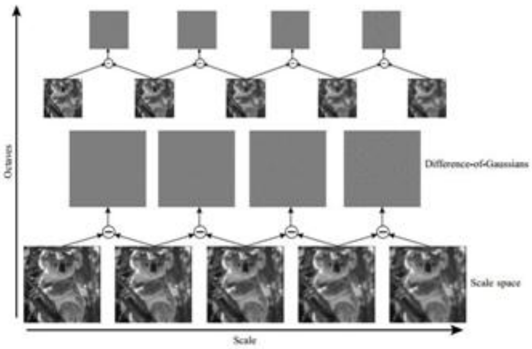

Fig 2: The construction of scale space extrema based on difference-of-Gaussians. [12]

B. Key point Location:

Once a key point candidate has been found, the next step is to adjust its accuracy. For all interest point's detailed model is created to determine location and scale. The Key points are selected based on their stability. A stable key point is thus a key point resistant to image distortion. Invariant features are always detected in the maximum or minimum of the D matrix which is the key points. In order to detect the extrema, we need to find the point which drives the second order derivative of D to be 0. Better results are obtained by interpolating than by taking center of cell as location.

Taylor expansion formula is used for this purpose:

$$D(x) = D + \frac{dD^t}{dx} X + \frac{1}{2} X T \frac{d^2 D}{dx^2} X \qquad (4)$$

Where D is the difference of Gaussian.

Then the extrema X is determined by

$$X = -\frac{d^2 D^{-1}}{dx2} \frac{dD}{dx}$$

To eliminate the edge effect and get the local extrema, use Hessian matrix and find the threshold.

H= Dxx Dxy

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Dxy Dyy

D_{xx} = D(x,y-1)-2D(x,y)+D(x,y+1)

D_{yy} = D(x-1,y)-2D(x,y)+D(x+1,y)

D_{xy} = D(x,y-1)-2D(x,y)+D(x-1,y)-D(x-1,y-1)

$Tr(H)= D_{xx} + D_{yy} =a +B;$

$Det(H)= D_{xx}D_{yy}-(D_{xy})^2 =a*B;$

$Ratio= (a+ B)^2 /a*B;$ (5)

Compute the Hessian matrix for each key point selected by second order derivative of D and remove the key point which is less than ratio [4].

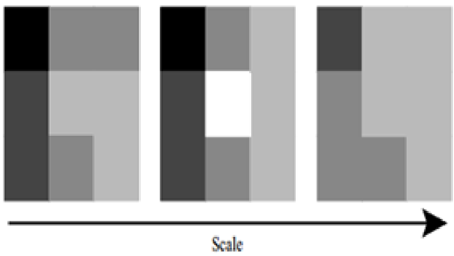

Fig 3: Key point localization at different scales

C. Orientation Assignment:

For each of the key points identified the SIFT computes the direction of gradients around. One or more orientations are assigned to each key point based on local image gradient directions. By assigning a consistent orientation to each key point based on local image properties, its feature vector can be represented relative to this orientation and therefore achieve invariance to image rotation. This key point orientation is calculated from an orientation histogram of local gradients from the closest smoothed image L(x, y, σ). For each image sample L(x, y) at this scale, the gradient magnitude m(x, y) and orientation θ(x, y) is computed using pixel differences:

m (x, y) = SQRT { ((L(x + 1, y) − L(x − 1, y))2+ (L(x, y + 1) − L(x, y − 1))2)½ }

$\theta (x, y) = \tan^{-1} ((L(x, y + 1)-L(x, y-1))/ (L(x + 1, y) - L(x - 1, y)))$ (6)

The orientation histogram has 36 bins covering the 360 degree range of orientations. Each point is added to the histogram weighted by the gradient magnitude, m(x, y), and by a circular Gaussian with σ variance that is 1.5 times the scale of the key point. Additional key points are generated for key point locations with multiple dominant peaks whose magnitude is within 80% of each other. The dominant peaks in the histogram are interpolated with their neighbors for a more accurate orientation assignment [4].

D. Key point Descriptor:

The local image gradients are measured at the selected scale in the region around each key point. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination. Figure 4 illustrates the computation of the feature vector of each key point.

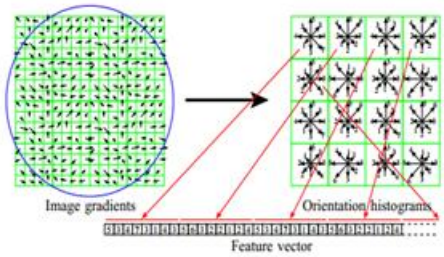

Fig 4. The computation of the feature vector of a key point [12].

Alternately, Principal component Analysis (PCA) algorithm is used for classification. Various researches have been done on PCA algorithm that provides more accurate image classifier system than other techniques. The main work of PCA is to extract principal features of an image. These principal features are integrated in predefined class or a single module. Various researchers analyses that the PCA based technique provide better classification and accurate output in the field of computer vision like weather forecasting, face identification, face recognition, feature based image classification, medical diagnostics, remote sensing images, data mining. [17] PCA is a technique which uses sophisticated underlying mathematical principles

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to transform a number of possibly correlated variables into a smaller number of variables called principal components. It is one of the most important results from applied linear algebra. The advantage of PCA is finding the patterns in the data and compressing data by reducing the number of dimensions without loss of information. The mathematical concepts that are used for PCA are Standard Deviation, Variance, Co–variance and Eigenvectors. The database images belonging to same category may differ in lighting conditions, noise etc., but are not completely random and in spite of their differences there may present some patterns. Such patterns could be referred as principal components. PCA is a mathematical tool used to extract principal components of original image data. These principal components may also be referred as Eigen images. An important feature of PCA is that any original image from the image database can be reconstructed by combining the Eigen images. The algorithm to calculate Principal Components is as follows.

STEP 1: Prepare the data:

Let us assume we have Xi, contain N vectors of size M (rows of image columns of image) representing a set of images and P represents a pixel values.

Xi = (Pi …..Pm), 1…..N (7)

STEP 2: Obtain the Mean.

Calculate the mean of the image vector and then set of images are mean centered according to subtract the mean image from every image vector.

Mean T_m = 1/M (Sigma K=1 to M, Xi) (8)

STEP 3: Mean is subtracted from the original image.

Tm = T_m-Xi (or) A = T_m-Xi (9)

Where, A is the new matrix constructed by subtracting mean of image from the original data.

STEP 4: Calculate the covariance matrix.

Let e’s and i’s are the eigenvectors and eigenvalues of the covariance matrix C, and this covariance matrix is calculated by multiplying matrix A with its transposing matrix of A.

$C = A * A^t$

STEP 5: Eigenvectors and Eigenvalues of covariance matrix are calculated and principal components selected.

The eigenvectors are sorted in descending order with their corresponding eigenvalues. The eigenvector associated with the largest eigenvalue is the one that reflects the greatest variance in the image. The number of highest valued eigenvectors is then picked to make an image space from the resultant covariance matrix C [14][16[17].

IMPLEMENTATION AND RESULTS:

A. MATLAB:

CBIR (SIFT or PCA) is coded using MATLAB programming language and implemented on a 2.00GHz CPU computer with 3.0GB RAM and Windows XP/Windows 7 operating system. The dataset used in the experiment is the MPEG-7 Core. It was created by the Motion Picture Expert Group (MPEG) committee which is a working group of ISO/IEC. We have taken a sample of this database for our execution with 75 binary images and 5 different image categories of 15 samples each. Grayscale image database called COIL-20, this image collection includes 1400 binary images grouped into 20 categories by their content and each category contains 70 image samples. The color database used for testing includes 5 different images each of 15 samples resulting in 75 total color images. Implementations of CBIR using SIFT and PCA methods are performed broadly under three major steps - Feature detection, Feature matching and indexing and retrieving results.

1) Feature Detection:

SIFT Approach: In Feature detection for SIFT, key point descriptors are identified using the SIFT algorithm for query image and all database images separately. For example an ‘octopus’ binary image gives 62 key points while a ‘hammer’ image gives

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only 13 key points as octopus image has more corners and edges. PCA Approach: In case of PCA, the first step is to pre-process the query image. After pre-processing, color feature, texture feature and shape features will be extracted using color moment model into HSV color space, then GLCM matrix and Fourier descriptor transformation are applied. After feature extraction the PCA calculates principal components from features of both query image and all database images and then classifies the query image to its respective class. The classification method PCA makes our retrieval system to more effective and robust. For testing query image using PCA, each image is examined and located its principal features. All the steps of the PCA algorithm outlined above are executed.

2) Feature Matching And Indexing:

In Feature matching and Indexing step, key point vector from a query image and key points vectors from database images are matched and verified for the closest Euclidean distance between them. According to the Euclidean distance formula, the distance between two points in the plane with coordinates (x, y) and (a, b) is given as:

$$\text{Dist}((x, y), (a, b)) = \text{SQRT}((x-a)^2 + (x-b)^2) \qquad (10)$$

Both SIFT and PCA utilize Euclidean distance formula for image matching.

3) Retrieving Results:

After feature detection and feature matching, during the retrieval process, key point feature descriptors of the query image are compared to those of the images in the database and ranked based on the most matches. Only top 10 of the matched images are displayed here in our experiment for testing [3][12].

B. OBSERVATIONS AND RESULTS:

The Performance of Image Retrieval using SIFT or PCA method is evaluated using Precision and Recall graphs. In the paper, we have experimented our code on 3 different Image databases. SIFT code is run on binary images, Grayscale images and color images. The results were captured separately for each database category and observations noted. PCA code is run on color database images and results were tabled. A comparison of PCA and SIFT results is analyzed for color images and a certain important comparisons are identified. Precision Vs Recall graph or sometimes referred to as PR graph, which is a standard evaluation method in document retrieval and have been popularly utilized in image retrieval. The precision and recall rates are defined as:

Precision Rate:

$$\frac{\text{Number of relevant image selected}}{\text{Total number of retrieved images}}$$

Recall Rate:

$$\frac{\text{Number of relevant images selected}}{\text{Total number of similar images in the database}}$$

(i) SIFT for Binary Images:

It has been observed that Images with more corners (like Octopus, tree) are retrieved with greater precision in SIFT, while the precision for images like hammer, spoon etc with less corners has reduced precision. It has been observed that Precision and recall rate for SIFT is good even when the images are rotated (hammer) or translated (apple) or of varied scales (octopus). SIFT has been able to retrieve affine images also with decent precision.

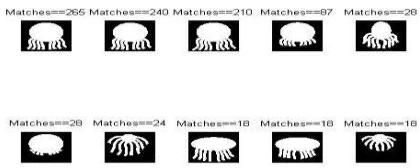

Fig 5: SIFT retrieved results for query Image 'Octopus'.

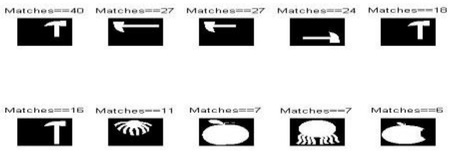

Fig 6: SIFT retrieved results for Image 'Hammer' rotated.

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Here is the precision Recall table for SIFT for Binary Images:

SNO	Image Class	Precision	Recall
1	Octopus	0.90	0.129
2	Hammer	0.70	0.10
3	Spoon	0.65	0.085
4	Apple	0.65	0.085

(ii) Comparison between SIFT and PCA:

In order to compare SIFT and PCA approaches, Color Images database is utilized and results retrieved for SIFT and PCA are analyzed. While both the approaches retrieve images and provide different results a few observations are noted for comparison.

SIFT for Color Images:

SIFT shows a better precision and recall rate when compared to PCA for color images.

Fig 7: SIFT retrieval for query image 'elephant'

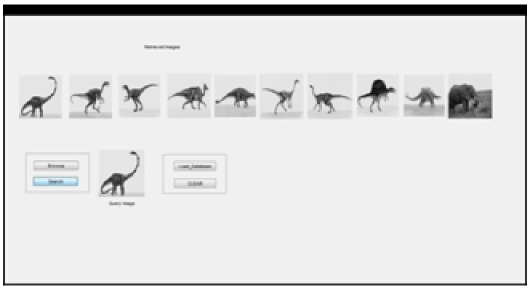

Fig 8: SIFT retrieval for query image 'Dinosaur'

PCA for Color Images:

PCA produces a decent precision and recall rates for Color Image retrieval.

Fig 9: PCA retrieval for query image 'elephant'.

Fig 10: PCA retrieval for query image 'flower'.

Below are a few Precision and Recall graphs for SIFT Vs PCA.

SIFT P/R table for Color Images

S.NO	Image Class	Precision	Recall
1	Elephant	0.80	0.145
2	Flower	0.70	0.10
3	Bus	0.40	0.05
4	Dinosaur	0.90	0.129

PCA P/R table for Color Images

SNO	Image Class	Precision	Recall
1	Elephant	0.65	0.085
2	Flower	0.70	0.10
3	Bus	0.50	0.07
4	Dinosaur	0.80	0.145

Observations:

SIFT provides better Image retrieval for Binary and Grayscale Images. SIFT has greater precision for Binary Images with Scale Invariance, i.e. Same images of different sizes are retrieved with more accuracy in SIFT than PCA.

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SIFT has better Image retrieval for Rotated Images. SIFT has better performance on Transposed Images. SIFT and PCA both work good on Color Images. However, SIFT algorithm shows a comparative advantage in precision and recall for Color Images against PCA algorithm. This is due to the fact that even though Color Images are affined, changes to illumination, different in sizes, SIFT works better than PCA. For example, images like elephants and dinosaurs where the database images vary in size, rotated and are affined, SIFT performs better than PCA. PCA works better than SIFT for Images whose principal components of shape are highlighted and similar between query and database Image, for example of 'Bus' image. Bus has a higher retrieval rate in PCA in comparison with SIFT. Hence PCA is used in face recognition software. Overall, it has been observed that under most of the conditions that an Image can be subjected to, SIFT is a better option.

CONCLUSION AND FUTURE SCOPE:

This paper has presented an effective way of Content based Image Retrieval (CBIR) using SIFT algorithm. The algorithms described in the paper are particularly useful due to their distinctiveness which enables for correct match for a key point to be selected from a set of large Image database. SIFT retrieves images with better performance that have more corners and edges, varying in size, Images that are transposed, rotated, affined etc. when compared to PCA. Otherwise PCA is a good alternative approach for color Image retrieval in CBIR. Overall, the project helps us in driving out a comparative study of SIFT and PCA methods for CBIR under various image conditions and circumstances. Future work will look at more efficient parameterization of feature descriptors and alternative methods and algorithms for better retrieval performance.

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