WAVELET BASED FEATURES FOR COLOR TEXTURE CLASSIFICATION WITH APPLICATION TO CBIR

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Abstract
This paper describes an algorithm for texture feature extraction using wavelet decomposed coefficients of an image and its complement. Four different approaches to color texture analysis are tested on the classification of images from the VisTex database. The first method employs multispectral approach, in which texture features are extracted from each channel of the RGB color space. The second method uses HSV color space in which texture features are extracted from the luminance channel V and color features from the chromaticity channels H and S. The third method uses YCbCr color space, in which texture features are extracted from the luminance channel Y and color features from the chromaticity channels Cb and Cr. The last one uses gray scale texture features computed for a color image. The classification results show that the multispectral method gives the best percentage of 97.87%. Further, this multispectral method for texture classification is applied to RBIR system. Experiments are carried out on Wang's dataset using JSEG for segmentation. The results are encouraging. Experiments are also carried out to study the effect of segmentation on the retrieval performance.
Key words:
Texture, wavelet transform, classification, feature extraction, RBIR.

1. Introduction

Textures provide important characteristics for surface and object identification from aerial or satellite photographs, biomedical images and many other types of images. Texture analysis is fundamental to many applications such as automated visual inspection, biomedical image processing, Content Based Image Retrieval (CBIR) and remote sensing. Much research work has been done on texture analysis, classification, and segmentation for the last four decades. Despite these efforts, texture analysis is still considered an interesting but difficult problem in image processing. Although the concept of texture was difficult to define, the studies showed that spatial statistics computed on the grey levels of the images were able to give good descriptors of the perceptual feeling of texture[9,22]. Such textural descriptors are more powerful tools for classification tasks or segmentation problems[14]. Over the past decade, the study of texture has been extended to the study of texture in color images. Approaches used for gray scale images are adapted to take into account the color information. The texture features are computed taking the correlations between the color bands into account. Descriptors are computed both within and between channels to give information on the whole color texture[15,16,17,21]. In the joint color-texture features[4,5,11], textural features(grey scale) and color features(moments or histograms for example) are computed individually and then are used together as the basis of a classifier.

Briefly stated, there are a finite number of classes Ci, i = 1,2,3,. . ., n. A number of training samples of each class are available. Based on the information extracted from the training samples, a decision rule is designed which classifies a given sample of unknown class into one of n classes. To design an effective algorithm for texture classification, it is essential to find a set of texture features with good discriminating power. The wavelet methods offer computational advantages over other methods for texture classification [1,2,10,19]. Unser[20] indicated that the choice of a filter bank in the wavelet texture characterization could be an important issue, possibly affecting the quality of texture description. Theoretical and implementation aspects of wavelet-based algorithms are well studied in [6, 7, 12, and 18].

Content Based Image Retrieval (CBIR) has been a very active research area since 1990's. The goal of CBIR is to retrieve desired images from large image databases, based on the image contents. Region Based Image retrieval (RBIR) is a special type of CBIR. A region is seen as a part of an image with homogeneous low-level features. Depending on the query specification type, the RBIR systems are categorized as Whole Image as Query(WIQ) and Image Region as Query (IRQ). In WIQ type RBIR, users provide the example image and the system uses information from the whole image for query. An image is segmented into regions that serve to represent the image. The similarity measure of two images is computed using feature information of regions of the whole image. The SIMPLIcity system [23] uses this type of approach, named as Integrated Region Matching (IRM), for image similarity. In IRQ type RBIR, a query is performed by choosing regions of the example image. The RBIR system responds by retrieving images containing similar region as that of the query regions. In

Blobworld[3], each region of an image is a blob associated with color and texture descriptors. Only a region of interest can be given as a query rather than giving whole image as query. To a large extent, the performance of RBIR depends on the precision of segmentation algorithm.

Thus the objective of present investigation is two fold: firstly, to extract wavelet based color texture features and secondly, to demonstrate the robustness of the feature set so obtained for RBIR and analyze the retrieval performance.

This paper is organized as follows: In the Section 2, wavelet decomposition is briefly discussed. In Section 3, the proposed work is discussed. In Section 4, the texture training and classification are explained. In Section 5, experimental results are discussed. In Section 6, application to CBIR is discussed in detail. Finally, conclusion is given in Section 7.

2. Wavelet Decomposition

The continuous wavelet transform of a 1-D signal f(x) is defined as

$$(W_a f)(b) = \int f(x)\Psi^*_{a,b}(x)dx \qquad (1)$$

where the wavelet $\Psi_{a,b}$ is computed from the mother wavelet Ψ by translation and dilation,

$$\psi_{a,b}(x) = \frac{1}{\sqrt{|a|}}\psi((x-a)/b) \qquad (2)$$

under some mild assumptions, the mother wavelet Ψ satisfies the constraint of having zero mean[7].

The eq. (1) can be discretized by restraining a and b to a discrete lattice ($a = 2^b, b \in \ell$). Typically it is imposed that the transform should be non-redundant, complete and constitutes a multiresolution representation of the original signal. The extension to the 2 – D case is usually performed by using a product of 1 – D filters. In practice, the transform is computed by applying a separable filter bank to the image:

$$\begin{aligned} A_n &= [H_x * [H_y * A_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n1} &= [H_x * [G_y * A_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n2} &= [G_x * [H_y * A_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \\ D_{n3} &= [G_x * [G_y * A_{n-1}]_{\downarrow 2,1}]_{\downarrow 1,2} \end{aligned} \qquad (3)$$

where * denotes the convolution operator, ↓2,1(↓1,2) denotes the down sampling along the rows (columns) and $A_0 = I$ is the original image, H and G are low pass and high pass filters, respectively. The A_n is obtained by low pass filtering and is referred to as the low resolution(Approximation) image at scale n. The D_{n1}, D_{n2}, D_{n3} are obtained by band pass filtering in a specific direction(Horizontal, Vertical and Diagonal, respectively) and thus contain directional detail information and is referred to as high resolution(Detail) images at scale n. The original image I is thus represented by a set of sub images at several scales. This decomposition is called "Pyramidal wavelet transform" decomposition or discrete wavelet decomposition (DWT). Every detail sub image contains information of a specific scale and orientation. The spatial information is retained within the sub image.

In the present paper, the features are obtained using Haar Wavelet (Fig. 1.), which is given by

$$\psi(t) = \begin{cases} 1 & 0 <= t <= ½ \\ -1 & ½<=t<=1 \\ 0 & \text{otherwise} \end{cases} \qquad (4)$$

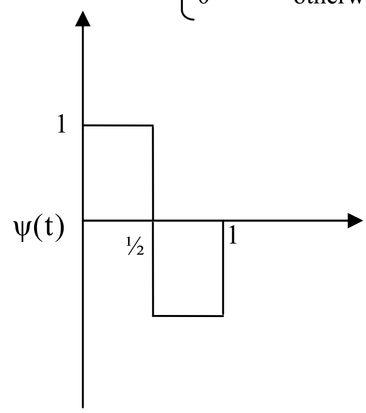

Fig. 1. Haar Wavelet representation

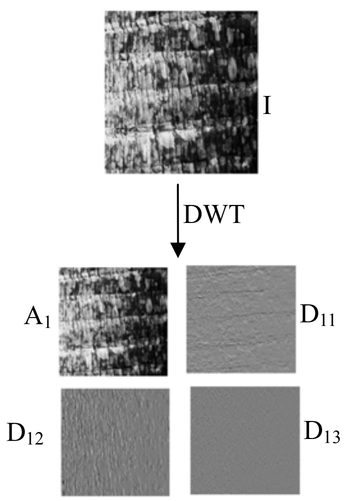

Fig. 2. Wavelet Decomposition of an Image(I)

As is required, $\psi(t)$ integrates to zero. One-level decomposition is performed on image I, which yields approximation image (A_1) and horizontal, vertical and diagonal detail images (D_{11}, D_{12}, D_{13}) as shown in Fig. 2.

3. The Proposed Work

3.1 Feature generation

The proposed work consists of extracting wavelet based features from each texture block of an image. It is an extension of the cooccurrence histogram method to multiresolution images. The cooccurrence histograms are constructed across different wavelet coefficients of an image and its complement decomposed upto 1-level. The combinations considered are (A_1, D_{11}) , (A_1, D_{12}) , (A_1, D_{13}) , $(A_1, \text{abs}(D_{13} - D_{11} - D_{12}))$, $(\overline{A}_1, \overline{D}_{11})$, $(\overline{A}_1, \overline{D}_{12})$, $(\overline{A}_1, \overline{D}_{13})$ and $(\overline{A}_1, \text{abs}(\overline{D}_{13} - \overline{D}_{11} - \overline{D}_{12}))$.

The translation vector is denoted by t[d,a], where 'd' is the distance and 'a' is the angle. In our experiments we have considered a distance of 1(d=1) and eight angles (a = 0^0, 45^0, 90^0, 135^0, 180^0, 225^0, 270^0, 315^0). The schematic diagram is shown in Fig. 3.

The cooccurrence histograms for each combination, for each of the eight angles, are constructed yielding 16 histograms per pair. The feature set comprises 384 features in all with 3 features each computed from the normalized cumulative histogram i.e., 8 pairs x 16 histogram x 3 features.

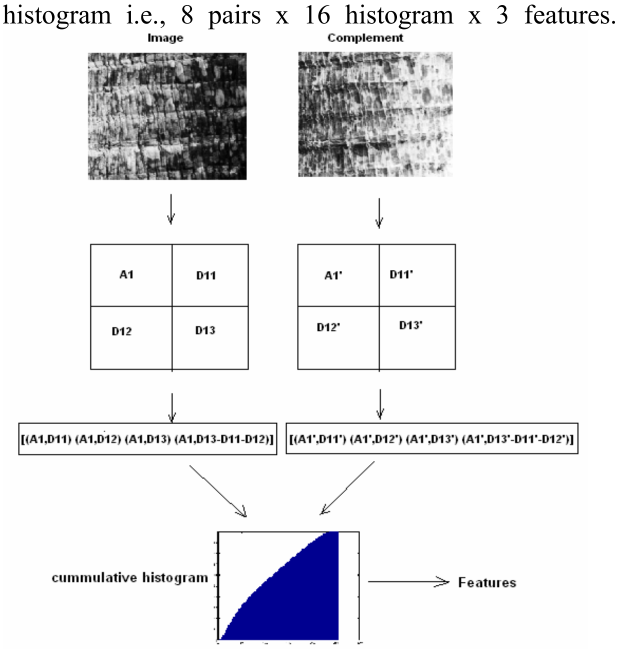

Fig. 3. Schematic diagram showing the proposed method

The method for histogram computation and feature extraction for one pair (A_1, D_{11}) for one angle i.e., 0 degree is presented below:

Histogram Computation

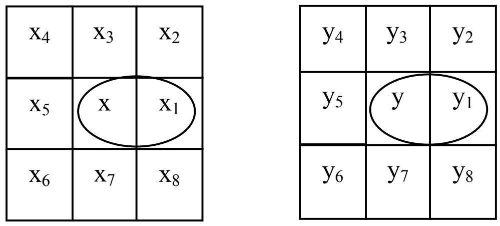

Fig. 4. 8-nearest neighbors of x and y in A_1 and D_{11} respectively

1. A pixel x in A_1 and a pixel y in the corresponding location in D_{11} are shown in Fig. 4 with their 8-nearest neighbors. The neighboring pixel of x and y considered for cooccurrence computation are shown by the circles in Fig. 4.
2. Construct two histograms H_1 and H_2 for A_1 based on the maxmin composition rule stated below:
   Let $\alpha = \max(\min(x,y_1), \min(y,x_1))$
   Then, $x \in H_1$, if $\alpha = \min(x,y_1)$
   and, $x \in H_2$, if $\alpha = \min(y,x_1)$
3. Repeat steps 1 and 2 for all pixels x in A_1.

Computing Features:

Three features are computed from every histogram as explained below:

1. Consider a histogram H.
2. Obtain cumulative histogram(CH) for H.
3. Normalize CH yielding NCH [13].
4. The points on the NCH($nch_1, nch_2, \ldots, nch_{256}$), are the sample points.
5. From the sample points, compute the following features:

   Slope: S_{nch} = Slope of the regression line fitted across the sample points.

$$\text{Mean:} \quad \mu_{nch} = \frac{\sum_{i=1}^{256} nch_i}{256} \tag{5}$$

$$\text{Mean Deviation:} \quad D_{nch} = \frac{\sum_{i=1}^{256} \left| nch_i - \mu_{nch} \right|}{256} \tag{6}$$

This procedure is illustrated in Fig. 5.

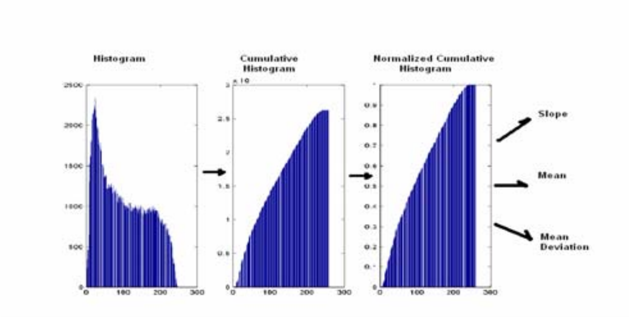

Fig. 5. Schematic diagram showing feature computation.

3.2 Multispectral method in RGB space

For a color image, the wavelet based features (Section 3.1) are computed on each of the channels R,G,B. It yields a total of 384x3 = 1152 features. A schematic representation is shown in Fig. 6

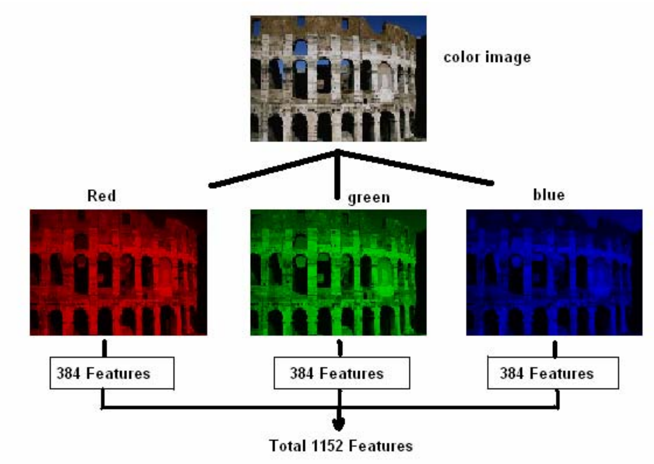

Fig. 6. schematic diagram showing the Multispectral approach in RGB space

3.3 Multispectral method in HSV and YCbCr spaces

In this approach, we use different color spaces, in order to obtain one channel containing the luminance information and two others containing chrominance information. Texture features are then computed from the luminance channel. The first order statistical features namely, mean and standard deviation, are computed from the chrominance channel:

$$\text{Mean(m)} = \frac{1}{N^2}\sum_{i,j=1}^{N} p(i,j) \qquad (7)$$

$$\text{Standard Deviation(sd)} = \sqrt{\frac{1}{N^2}\sum_{i,j=1}^{N}\left[p(i,j)-m\right]^2} \qquad (8)$$

This method yields 384+2+2 = 388 features and is tested on HSV and YCbCr color spaces. Firstly, the HSV (hue, saturation, value) color space was used. It corresponds better to how people experience color than the RGB color space does: hue(H) represents the wavelength of a color if it were monochromatic. Hue varies from 0 to 1 when color goes from red to green then to blue and back to red. H is then defined modulo 1. As color is seldom monochromatic, saturation (S) represents the amount of white color mixed with the monochromatic color. Value(V) does not depend on the color, but represents the brightness. So H and S represent chrominance and V is intensity.

The following equations transform RGB in [0,1] to HSV in [0,1]:

$$V = \max(R,G,B) \qquad (9)$$

$$S = \frac{V - \min(R,G,B)}{V} \qquad (10)$$

$$H = \frac{G-B}{6S}, \text{ if } V=R \qquad (11)$$

$$H = \frac{1}{3} + \frac{B-R}{6S}, \text{ if } V=G \qquad (12)$$

$$H = \frac{2}{3} + \frac{R-G}{6S}, \text{ if } V=B \qquad (13)$$

Secondly, we use the YCbCr color space, which is widely used for digital video. In this format, luminance information is stored as single component(Y), and chrominance information is stored as two color difference components(Cb and Cr). Cb represents the difference between the blue component and a reference value. Cr represents the difference between the red component and a reference value. These features are defined for video processing purposes and so are not meaningful for human perception.

The following equations transform RGB in [0,1] to YCbCr in [0,255].

$$Y = 16+65.481R+128.553G+24.966B \qquad (14)$$

$$Cb = 128-37.797R-74.203G+112B \qquad (15)$$

$$Cr = 128+112R-93.786G-18.214B \qquad (16)$$

The Fig. 7 shows the feature generation schematically.

3.3 Gray scale method

In this method the color image is converted to a gray scale image.

$$I = \max(R,G,B) \qquad (17)$$

No color information is coded. The texture features are computed on the gray scale image. This method yields 384 features. The schematic representation is shown in Fig. 8.

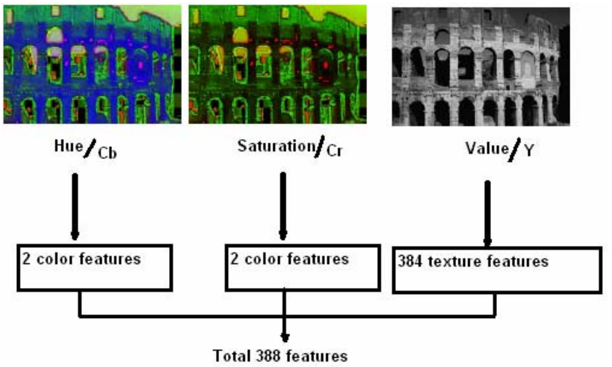

Fig. 7. Schematic diagram showing Multispectral approach in HSV/YCbCr space

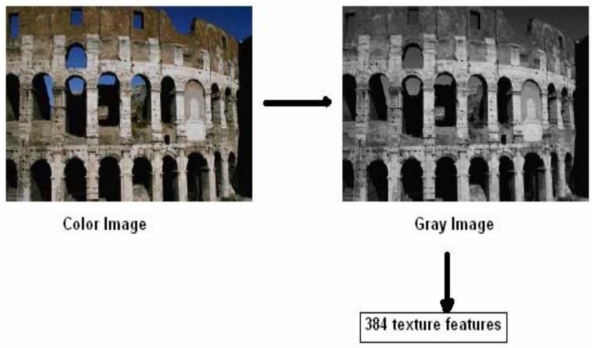

Fig. 8. Schematic diagram showing the texture features for gray scale method

4. Texture training and classification

For experimentation, the data set consists of texture images, each of size 512x512 obtained from VisTex(1995) color image data base (Fig.9)[25]. Each texture image is subdivided into 64 equal sized blocks out of which 32 randomly chosen blocks are used as samples for training and remaining blocks are used as test samples for that texture class.

4.1 Training

In the texture training phase, the texture features (described in Section 3) are extracted from the 32 samples selected randomly belonging to each texture class, using the proposed feature extraction method. These features are stored in the feature library, which are further used for texture classification.

4.2 Classification

In the texture classification phase, the texture features are extracted from the test sample x using the proposed feature extraction algorithm, and then compared with the corresponding feature values of all the texture classes k stored in the feature library using the distance vector formula,

$$D(M) = \sqrt{\sum_{j=0}^{N}\left[f_j(x) - f_j(M)\right]^2} \qquad (18)$$

where, N is the number of features in f, $f_j(x)$ represents the j^{th} texture feature of the test sample x, while $f_j(M)$ represents the j^{th} feature of M^{th} texture class in the library. The test texture is classified using the K-nearest neighbors (K-NN) classifier.

In the K-NN classifier, the class of the test sample is decided by the majority class among the K nearest neighbors. A neighbor is deemed nearest if it has the smallest distance in the feature space. In order to avoid a tied vote, it is preferable to choose K to be an odd number. The experiments are performed choosing K=3.

Fig. 9. Texture images
From left-right and top - bottom: Bark.006, Brick.0000, brick.0004, Clouds.0001, Fabric.0013, Fabric.0017, Flowers.0006, Food.0000, Food.0001, Grass.0001, Leaves.0012, Metal.0002, Metal.0004, Misc.0001, Misc.0002, Sand.0000, Sand.0002, Tile.0008, Water.0005, Wood.0002

5. Experimental Results and Discussion

The experimental results of the proposed method in different color spaces are compared in the Table.1, which shows the percentage classification for different image classes. The analysis of the experimental results shows that, in general, classification accuracy 97.87% is achieved with the multispectral method in RGB space, followed by HSV (94.22%), YCbCr (92.97%), in comparision with gray scale method (92.03%). However, in case of Sand(No. 16), Water(No.19) and Wood(No. 20), HSV color space has yielded better classification results(100%) than RGB space. Extensive experiments are carried out with different wavelets. However, Haar wavelet yielded better results compared to other wavelets[26], since it transforms the pixels using two-filter classes, one of positive energies and other of negative energies, and thus renders better histogram classification employed in our algorithm.

Table 1. Results of texture classification using the proposed method

Sl.No	images	Correct Classification(%)			
		RGB	HSV	YCbCr	Gray
1	Bark.0006	92.625	68.75	84.375	90.625
2	Brick.0000	100	84.375	90.625	87.50
3	Brick.0004	100	87.5	100	100
4	Clouds.0001	100	100	100	90.625
5	Fabric.0013	100	100	100	100
6	Fabric.007	100	100	100	100
7	Flowers.0006	96.875	71.875	93.75	96.875
8	Food.0000	100	96.875	100	96.875
9	Food.0001	100	100	100	100
10	Grass.0001	94.825	87.50	56.25	62.5
11	Leaves.0012	100	96.875	84.375	100
12	Metal.0002	100	93.75	100	100
13	Metal.0004	100	96.875	100	96.875
14	Misc.0001	100	100	100	100
15	Misc.0002	100	100	90.625	93.75
16	Sand.0000	95.125	100	100	68.75
17	Sand.0002	100	100	96.875	100
18	Tile.0008	100	100	100	100
19	Water.0005	90.625	100	93.75	84.375
20	Wood.0002	87.375	100	68.75	71.875
Mean Success rate		97.87	94.22	92.97	92.03

6 Application to CBIR

We have applied the multispectral method for RBIR in RGB space. The detailed results are furnished in the following sections.

6.1. Image set

The image set used for experimentation is WANG database[24] which is a subset of Corel images consisting of 1000 images of natural scenes divided into 10 labeled categories of 100 images each.

6.2. Segmentation algorithm

JSEG[8] segmentation algorithm is used for segmenting the images. The default settings of the algorithm are used. A total of 17771 regions are generated by the algorithm averaging 17.8 regions per image. The segmentation algorithm was run on a Pentium-IV, 1.7GHz processor with 128MB of RAM. It takes on an average a minute per image amounting to 16.6 hours of computation time.

6.3. Computation of features

Since the feature set is to be computed for every region of the image for each channel, the computation time is slightly higher. On an average, on a Pentium-IV, 1.7GHz processor with 128 MB RAM and Matlab 6.1, it took 8.9 minutes per image for feature computation amounting to almost 149 hours of computation time. This experiment had to be carried out in parts to accomplish the task. While computing cooccurrence histograms of a region, the correlation of pixels $P_i \rightarrow P_j$ is considered (for distance 1 and any direction) if both P_i and P_j belong to the same region.

6.4. Normalization

Every feature was normalized using the standard deviation of that feature over entire database. i.e. $f_i = f_i / \sigma(f_i)$, where f_i is the i^{th} feature in the feature set and $\sigma(f_i)$ is the standard deviation of f_i over the entire image database. The results improved considerably with this normalization. In addition to this, the feature set was normalized using the unit vector normalization.

6.5. Indexing

A full scan method over the database was carried out to achieve the retrieval efficiency. Indexing is done using a simple data structure like array to hold the regions. In order to analyze the effect of segmentation on retrieval performance, the experiments were carried out in 4 stages, with different number of regions, omitting all the regions below a cutoff size every time. The first experiment was with all the regions i.e. 17771. In the second experiment all the regions, with size less than 3% of the image size, were eliminated. A total of 5454 regions were left in the data structure. Third experiment filtered all regions less than 6% of the image size. The data structure size further shrunk to 3562. Lastly, all the regions less than 9% were eliminated resulting in just 2717 regions.

6.6. Query set

A total of 10 queries with ground truth were formulated. Even though a categorization is available on the WANG database, this query ground truth formulation was necessary because of wide variety of color options available in the same category. For example in the buses category we have Red, Green, Yellow and Blue buses. Similarly in roses category we have Red, Yellow, Pink and white roses. This process was manually carried out by grouping images based on visual perception. The query answer time varied with the number of regions contained in the data structure. The 10 intervals of recalls were recorded and the results are presented for full recall.

6.7. Effect of segmentation

The Fig. 10 shows a precision ~ recall graph with the averaging done over all the queries for different sized filters applied to the region database. It is evident that considering all the regions (with out filter) favors retrieval. This demonstrates the robustness of the feature set. However, 3% filtering does not alter the performance greatly. On the other hand, too much of filtering results in decrease retrieval performance, since the considerable amount of information is lost. In fact, it was observed that for the query on Horses category when 6% and 9% filters were applied, considerable information was lost. Regions belonging to most of the horses were eliminated resulting in poor performance. However, in case of grass and beach, the results were encouraging for large regions. Usage of merger option in the segmentation algorithm possibly could improve the performance. But the merger option provided with JSEG does not apply merging uniformly across different categories of images. For example, in the elephant categories, large regions of green patches were seen getting merged with elephant regions while attempting to merge the elephant regions. A similar type of merger was seen in case of merging white buildings with blue sky. Devising a common set of parameters for the segmentation algorithm for all the categories seemed difficult.

6.8. Precision Vs Recall

The precision ~ recall graphs for a few queries are shown in Fig. 11. In case of Yellow roses and the Grass land it can be seen that the performance of 6% and 9% filtering is clearly better than 3% filtering and no filtering results. Where as in case of elephant and white horse the results of 6% and 9% filtering are not satisfactory, but the results of 3% filtering and no filtering are considerably good. The effects of segmentation are seen to be devastating. One more observation made, which is worth mentioning, is different region filters can be used for different categories of queries. Though the system will have overheads, the overall retrieval performance can be improved.

6.9. Sample query

The Fig. 12 shows the sample queries and the first 10 retrievals for each query obtained by our proposed method. The first image in the list is the query region, followed by the corresponding retrieved images.

7. Conclusion

In this paper, a novel method for color texture classification, using wavelet based features obtained from an image and its complement, is presented. The experimental results obtained in different color spaces, namely, RGB, HSV and YCbCr are compared with that in gray scale. In general, RGB space provides better classification results. The Haar wavelets are used, since they are more effective in texture classification compared to other wavelets. Further, the robustness of the proposed feature set for color texture classification is demonstrated by its application to RBIR system. The experimental results demonstrate the efficacy of the proposed method for color texture classification. The results are encouraging.

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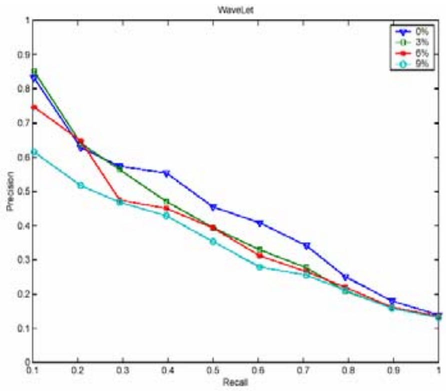

Fig. 10 Average Precision ~ Recall graph

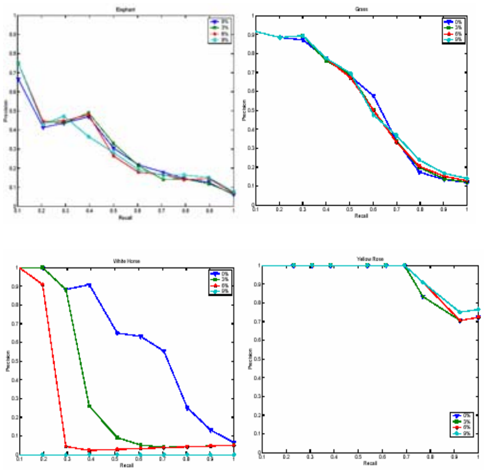

Fig. 11. Precision ~ Recall graphs. Top-left: Elephant, Top-right: Grass, Bottom-left: White Horse,

Bottom-right: Yellow Rose

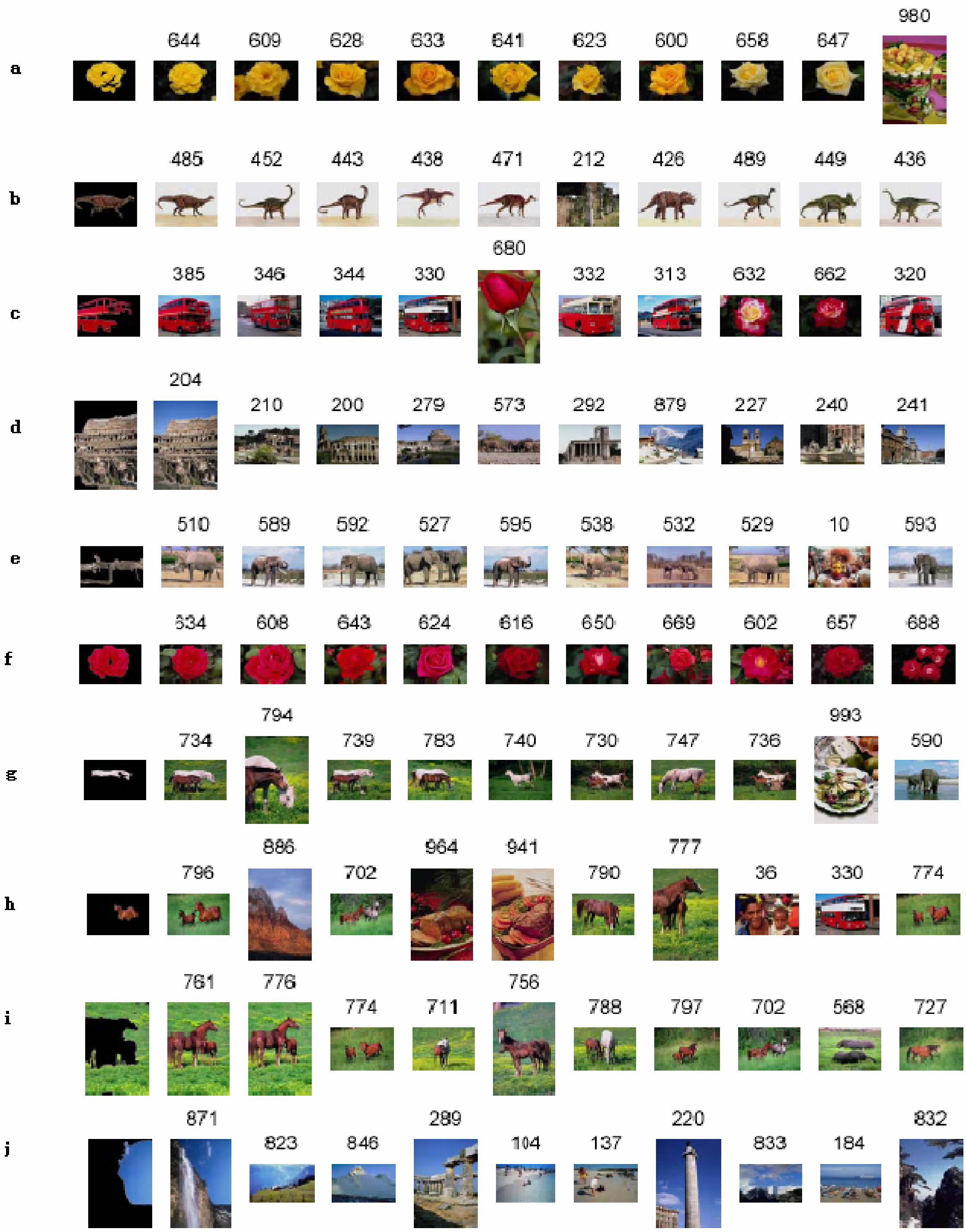

Fig. 12. Sample query region followed by top ten retrievals in ten examples. The correct retrievals are (a) 9, (b)9, (c)7, (d)8, (e)9, (f)all 10, (g) 8, (h)5, (i)all 10 and (j) all 10.

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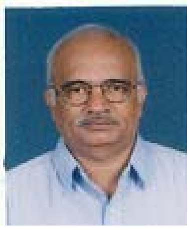

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