Color feature distribution for content based image retrieval

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Abstract: *Features have an important impact on the performance of image retrieval. Wherein spatial features such as shape, color are observatory content, spatial features are observed to more informative. To extract spatial features in image retrieval system, wavelet transformations were used. In conventional content based retrieval system color were taken as a basic feature for representation. However these color features are randomly concentrated on a image sample, and a direct color feature give variance in the color representation. Hence in this paper a color distribution feature using wavelet transformation is proposed. The utilization of wavelet transformation over color feature results in extraction color variation in spectral domain. This finer details give better feature representation of feature, resulting in improved retrieval performance.*

Keyword: Wavelet Transformation, Content based image retrieval, feature description.

I. Introduction

Content-based image retrieval systems are the very commonly used retrieval because of its efficient recognition and lower implementation complexity. Though these systems are basically lower in complexity the efficiency of the recognition accuracy is observed to be reducing when the images are spatial similar. The content information extracted are observed to be lower in information to retrieve such spatial information’s and the recognition matching is observed to be lower. To improve the recognition accuracy with retaining lower complexity and achieving higher accuracy various methods were proposed in past. Recent CBIR systems based on features like color, shape, texture, spatial layout, object motion, etc., are cited in [1], [2]. Of all the visual features, color is the most dominant and distinguishing one in almost all applications. Hence, segmenting color information’s provides prominent regions in the image. Shape features of these regions to obtain shape index used for retrieving based on shape matching were proposed in past. In Current CBIR systems such as IBM's QBIC [3], [4] allow automatic retrieval based on simple characteristics and distribution of color, shape and texture. But they do not consider structural and spatial relationships and fail to capture meaningful contents of the image in general. Also the object identification is semi-automatic. Many techniques such as chain code, polygonal approximations, curvature, Fourier descriptors, radii method and moment descriptors have been proposed and used in various applications [5]. This paper aims to improve these retrieval method efficiency by the integral approach of color information with wavelet based spectral decomposition for improved image retrieval. A specific color space analysis over spectral variation is suggested to improve the retrieval efficiency with lower complexity. For the retrial of the recognition system a generic model is proposed for image retrieval.

II. Content Based image retrieval

The image retrieval systems are computed with basically the content features of the image namely color, texture, or shape recognition. The color-based information are considered as the referencing index in this paper and the spectral variation for the color information is computed using discrete wavelet transformation technique. DWT are found to be a very efficient approach is extracting the frequency resolution information from the image information based on the input information. Where the resolution information was passed as additional information for retrieval in past, the incremental in the feature count result in computational complexity improvement. To achieve the objective of image retrieval, the operation is performed in two operational stages, training and testing. A Basic operational architecture for such a system is shown in figure 1.

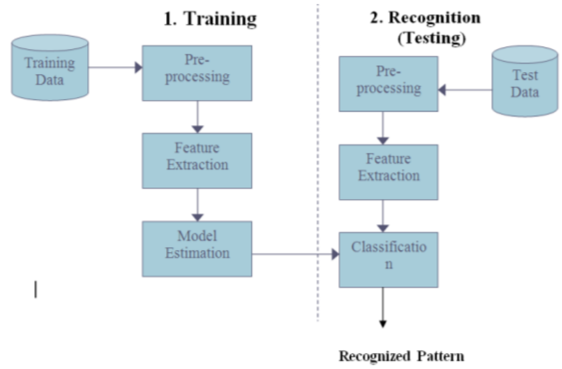


Figure 1: architecture of a content based image retrieval system

The samples are preprocessed for filtration, resizing and data precision. The pre-processed sample is then processed for feature extraction.

III. Color Feature Descriptor

The image retrieval systems are computed with basically the content features of the image namely color, texture, or shape recognition. The color-based information are considered as the referencing index in this paper and the spectral variation for the color information is computed using discrete wavelet transformation technique. DWT are found to be a very efficient approach is extracting the frequency resolution information from the image information based on the input information. Where the resolutional information was passed as additional information for retrieval in past, the incremental in the feature count result in computational complexity improvement. To have a retrieval efficiency improvement with current system in this paper an approach to retrieval based on the resolution of the color information is suggested. The system designed for the estimation is as shown below.

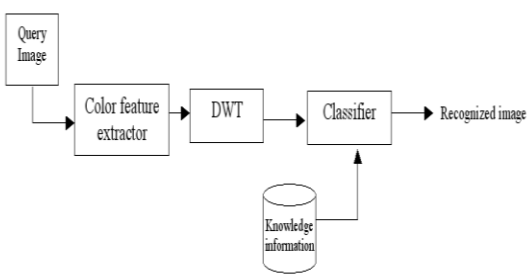


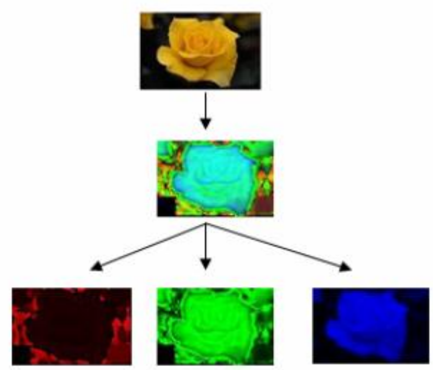
Figure 2: proposed recognition system

The color feature extraction is made with the color descriptor; a color quantization in RGB space using 25 perceptual color categories are employed. From the segmented image we find the enclosing minimum bounding rectangle (MBR) of the region, its location, image path, number of regions in the image, etc., and all these are stored in a metafile for further use in the construction of an image index tree. The entire RGB color space is described using a small set of color categories that are perceptual to humans. This is summarized into a color look-up table as depicted in table 1. A smaller set is more useful since it gives a coarser description of the color of a region thus allowing it to remain same for some variations in imaging conditions. We have taken a table of 25 perceptual colors chosen from the standard RGB color palette table.

Color	R	G	B	Color	R	G	B
Black	0	0	0	Plum	146	109	0
Sea green	0	182	0	Teal	146	182	170
Light green	0	255	170	Brown	182	0	0
Olive green	36	73	0	Magenta	182	73	170
Aqua	36	146	170	Yellow green	182	182	0
Bright green	36	255	0	Flour green	182	255	170
Blue	73	36	170	Red	219	73	0
Green	73	146	0	Rose	219	146	170
Turquoise	73	219	170	Yellow	219	255	0
Dark red	109	36	0	Pink	255	36	170
Blue gray	109	109	170	Orange	255	146	0
Lime	109	219	0	White	255	255	255
Lavender	146	0	170				

Table 1: Color look-up table

The method relies on the fact that boundaries where perceptual color changes occur must be found before any cluster in color space can be interpreted as corresponding to a region in image space. The RGB color space is partitioned into subspaces called color categories. The perceptual color of a pixel can be specified by the color category into which it maps.



R plane G plane B plane

Figure 3: the extracted color planar information

For the obtained color information a resolution transformation technique based on DWT Daubechies wavelet transformation is realized. According to the frequency analysis theory,there are several frequency channels perceived by the human visual system. Each of these frequency channels responses only to a limited bandwidth of the image constructed on the retina. Consequently, we can consider them as bandpass filters and it would be convenient to think of the visual system as a filter bank consisting of several filters, where each filter's response covers certain areas of the spatial frequency spectrum. In an image, a busy or sharp area consists of high frequency components and a smooth area contains lower frequency components. The flat areas can be associated with the interior of the objects or backgrounds while the busy areas can be textured surfaces or object boundaries. Physically, different frequency components in an image may be regarded to different objects or boundaries. As a result, judging the similarity of images by the human visual system can occur as follows: an image is decomposed into different frequency components and the corresponding components of different images are compared.

IV. Wavelet Transformation coding

The discrete wavelet transform is a very useful tool for signal analysis and image processing, especially in multi-resolution representation. In image processing, it is difficult to analyze the information about an image directly from the gray-level intensity of image pixels. The multi-resolution representation can provide a simple method for exploring the information about images. The two-dimensional discrete wavelet transform can decompose an image into 4 different resolutions of sub-bands. Those sub-bands include one average sub-bands and three detail component sub-bands. Detail component sub-bands represent different features for an image. Wavelets $\psi_{a,b}$ (x) are functions generated from mother wavelet ψ by dilations and translations

$$\psi_{a,b}(x) = |a|^{-1/2}\psi\left(\frac{x-b}{a}\right)$$

The basic idea of wavelet transform is to represent any function *f* as a superposition of wavelets. Using weighting coefficients, the wavelet can be decomposed as an integral over a range a and b of ψ (x). In a multi-resolution analysis, a scaling function ϕ(x) is employed to process the multi-resolution. The wavelet get decomposed into a $_{m,n}$ (f) called as approximate coefficients of a $_{m-1,l}$ and c $_{m,n}$ (f) termed as detail coefficients of a $_{m-1,l}$ using a low-pass and a high-pass filter in cascade. The two-dimensional decomposition is carried out by the combination of two one-dimensional decomposition of wavelet transform. Two-dimensional discrete wavelet transform can be achieved by two 1-D DWT operations performing operations isolately on rows and columns. Firstly the row operation is performed to obtain two sub-bands by using 1-D DWT, one low-pass sub-band (L) and one high-pass sub-band (H) as shown in Figure 4. The 1-D DWT image is transformed again to obtain four sub-bands by another 1-D DWT operation. Figure 4 shows the filter bank realization for the decomposition process of a 2-D DWT operation. The LL sub-band represents the approximate component of the image and other three sub-bands (LH,HL and HH) represent the detail components.

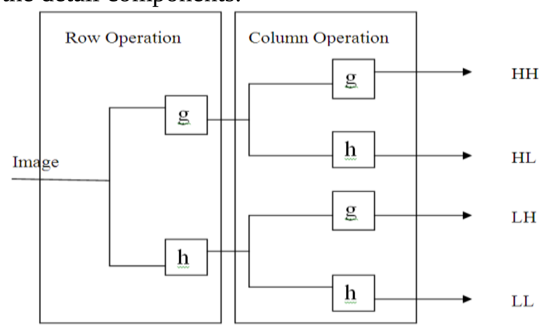


Figure 4: 2-Dimensional DWT Decomposition

This is a non-uniform band splitting method that decomposes the lower frequency part into narrower bands and the high-pass output at each level termed as detail coefficients are left without any further decomposition. This procedure is done for all rows. Next, the filtering is done for each column of the intermediate data. The resulting two-dimensional array of coefficients contains four bands of data, each labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high).

LL	HL
LH	HH1

Figure 5: Illustration of 1 scale decomposed coefficients

The LL band called as approximate coefficients can be decomposed once again in the same manner, thereby producing even more sub bands. This can be done up to a level of $\log_2$ (size max). The wavelet representation gives information about the variations in the image at different scales. In our retrieval context, we would like to extract salient points from any part of the image where "something" happens in the image at any resolution. A high wavelet coefficient (in absolute value) at a coarse resolution corresponds to a region with high global variations. The idea is to find a relevant point to represent this global variation by looking at wavelet coefficients at finer resolutions. A wavelet is an oscillating and attenuating function with zero integral. We study the image f at the scales of $1/2, 1/4, \ldots, 2^{j}, j \in$ □**Z.** the resolution decomposition of the color feature revels the color feature variation of the image.A Generic pyramidal decomposition architecture is been suggested for the spectral decomposition as shown,

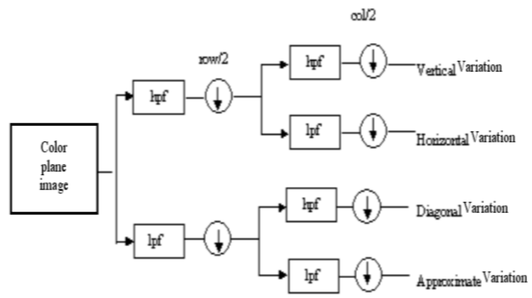


Figure 6: spectral decomposition of the color planar information

The color spectral decomposition is as observed below. The proposed work consists of extracting wavelet based features from each texture block of an image. It is an extension of the co-occurrence histogram method to multi-resolution images. The co-occurrence histograms are constructed across different wavelet coefficients of an image and its complement decomposed upto 1-level. The com1bina1t1ions considered are

(A_1, D_{11}) , (A_1, D_{12}) , (A_1, D_{13}) $(A_1, \text{abs}(D_{13} - D_{11} - D_{12}))$, $(\bar{A}_1, \bar{D}_{11})$, $(\bar{A}_1, \bar{D}_{12})$ $(\bar{A}_1, \bar{D}_{13})$ and $(\bar{A}_1, \text{abs}(\bar{D}_{13} - \bar{D}_{11} - \bar{D}_{12}))$.

The translation vector is denoted by t[d,a], where 'd' is the distance and 'a' is the orientation angle. The co-occurrence histograms for each combination, for each of the eight angles, are constructed yielding 16 histograms per pair. 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,

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

where, N is the number of features in $f_j(x)$, where j represents the j^{th} texture feature of the test sample x, while $f_j(M)$ represents the j^{th} feature of Mth 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.The classification of the feature vector is performed based on the Euclidian distance approach. For a given test image $Tr \sim \epsilon R^{m\times n}$ is transformed into a feature matrix $Yr\ \epsilon R^{r\times c}$. For the computed feature the distance between a test image T and a traning images $X_i^{(j)}$ is calculated by $R_{ji} = \delta(Y, X_i^{(j)}) = \|Y - X_i^{(j)}\|_F$, using a Frobenius norm. From the Retrieve top 8 subjects of the database according to the rank of R_{ji} given by arg Rank $_j\{R_{ji} = \delta(Y, X_i^{(j)}), 1 \le i \le N_j\}$. The image with the highest Rank is declared as the recognized image. For the evaluation of the image retrieval a performance analysis is carried out for spatial similar images and compared with the conventional color feature based retrieval system.

V. simulation observation

The experimental results of the proposed method in different color spaces are compared, 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%), Extensive experiments are carried out with different wavelet features which are transformed for the pixels using two-filter classes, one of positive energies and other of negative energies, and thus renders better histogram classification employed in the suggested algorithm. The obtained observations are as outlined below,

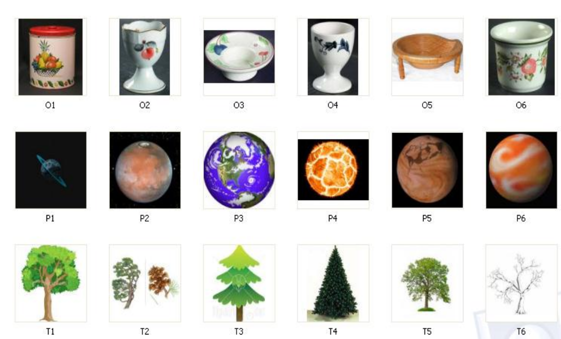


Figure 7: Training Dataset

For the designing of proposed CBIR unit, a set of randomly selected image sets are used. Few of the samples used for training is as shown in figure 7. A spatial similar objects with similar representation and having similar color feature is selected. Over this dataset a feature table is created using feature extraction logic. The obtained observations for few query samples are as shown in figure 8.

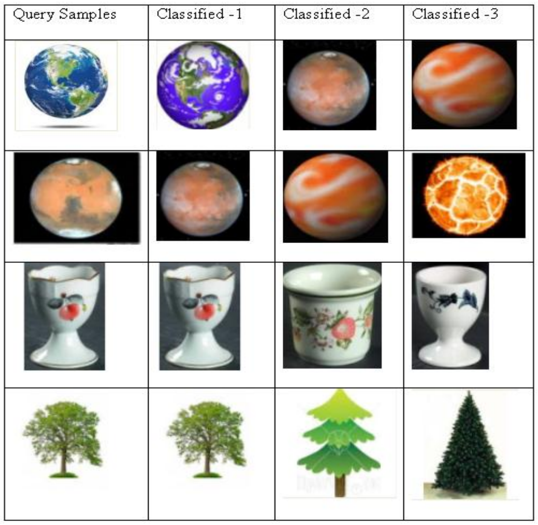


Figure 8: Classifications observation

It is observed that, for a give query sample, the best match samples are retrieved. The test is conducted for different spatial similar samples, a variation is given for the color representation and shape variation. The classification observation is observed to be very high for the given test sample. The recall rate for the developed Image transformed with color feature is outlined in figure 9.

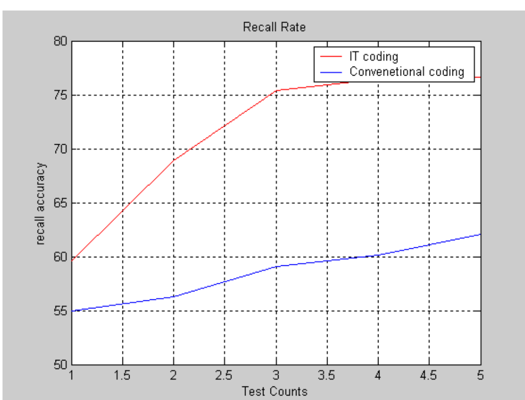


Figure 9: system recall rate

The recall rate for the developed system is presented in figure 9. The conventional coding using shape and color feature is compared with the proposed image transformed feature extraction approach.

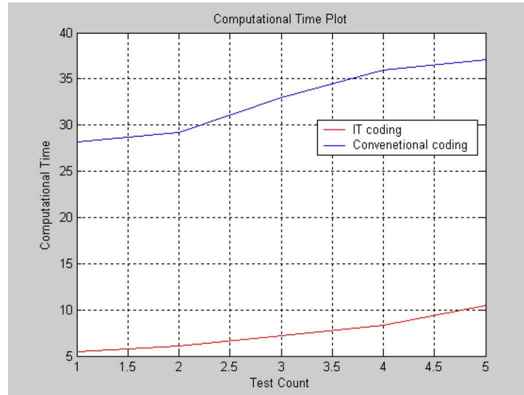


Figure 10: Computational time v/s test count

The time taken to perform a retrieval action is recorded for the two methods and compared. The computational time is observed to be higher for the conventional method due to larger number of feature counts, however such features are selectively taken in DWT based approach resulting in lower feature count and faster retrieval.

VI. Conclusion

A color feature based image retrieval coding is proposed. The image coding is based on the color feature representation and its variation in spectral domain. The features are observed to be more elaborative in finer scale resulting in higher recall rate. As well due to finer selection of feature coefficients, the number of feature coefficients are reduced which results in minimization of computation time.

VIII. References

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