F- Norm based Color Image Retrieval with Selective Relevance Feedback

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ABSTRACT

Image retrieval has become an important aspect in today's world as there is rapid growth of digital data day by day. It is required to have efficient search system with fast and accurate retrieval to cater to the need of end user with less computational cost and time. A new content based search system is required to address the problem. In this paper, a new method is proposed for color image analysis and retrieval based on F-norm theory is presented. Image Retrieval is carried out by the decomposition of images using complex wavelet transform and extracting the features of the image from low frequency channel using F-norm theory. A new way is suggested to further enhance the performance of the system with relevance feedback in which retrieval is carried by training only the selected query images from the database having poor retrieval accuracy.

Keywords

Complex Wavelet Transform, F-norm, Relevance feedback, Average Retrieval Accuracy

1. INTRODUCTION

With the wide spread use of internet, large number of users is able to access large amount of digital image data. Lot of advances is taken place in digital world over the past in many aspects of digital technology, especially improvement in devices for image acquisition, data storage and bitmapped printing and display etc. The key obstacle for many applications is the requirement to represent the digital image directly. The rapid growth of image database day by day is further creating the need to develop effective and efficient image retrieval systems. The color, texture and shape of the image play the most powerful role as features in most of the content based image retrieval systems. In a typical retrieval system, visual contents of the image are retrieved in the form of feature vector. The feature vector of each of the image in the database is extracted and stored. For a given query image, the features are extracted and compared with features of the database image for retrieval. In order to have efficient retrieval, it is necessary to capture the important characteristics of an image making it different from the other similar images.

The wavelet transform alleviates blocking artifacts present in DCT and its multi resolution characteristic in wavelet decomposition lead to superior energy compaction and good quality decompressed image [3]. Wavelet transform represents an image as a sum of wavelet functions (wavelets) with different resolutions and scales. The topic of multi resolution using wavelet transforms has received a great deal of attention in recent years. Wavelet transform play important role because they provide a means for localization of signals in both frequency and time. This leads to many applications such as image analysis, image compression, pattern recognition, image de noising etc.

Texture can be represented in many ways such as Tamura feature, SAR model, Gabor and Wavelet transformation [1]. Texture gradient is a popular way of extracting features used for content-based image retrieval (CBIR) of texture images [2]. Texture as a primitive visual cue has been studied for many years and it forms an important part of the visual world of animals and humans. The visual systems analyze texture areas present in the visual scene to identify homogenous regions. Thus, texture analysis is an essential element in visual information processing. Much of the research work has been done in this direction in terms of texture analysis, classification and segmentation. The study is further extended for texture in color images. The texture characteristics are extracted from color bands giving the information about color texture. [4, 5, 6] Methods have been proposed to extract the texture and color features from the moments of the histogram for joint color – texture feature extraction [7, 8].

Many algorithms have been developed using different techniques for the efficient extraction of color and texture features together. The wavelet approach has emerged as efficient over other methods because of its computational advantages. The different approaches can be conventional discrete wavelet transform, Gabor wavelet, M -band wavelets, tree structured wavelet transform, curve let transform etc. The standard DWT becomes inefficient in analyzing the high frequency signal with narrow bandwidth. It also lacks the sensitivity and directionality. The Gabor wavelet is not efficient as it introduces redundancy and memory requirement as the basis functions are not orthogonal. The M-band wavelet decomposition provide many sub bands which improves the retrieval accuracy but at the cost of more computational

complexity. Retrieval accuracy can be further improved by relevance feedback. Relevance feedback based on Nearest neighbor approach ranks each image with reference to relevance score based on nearest neighbor distance [9]. Another method uses markov model mediators frameworks to cluster the database to improve the performance of query processing and matching [10]. Region based image retrieval with relevance feedback is proposes a system which learns the importance of region for feedback from the user to improve the performance [11]. Image retrieval based on interactive approach in which retrieval accuracy based on modification of query features by user's feedback by providing weight of preference to relevant images [20]. In another method, inconsistency is measured from relevance feedback and combined with Bayesian classifier to build the overall criterion for feature selection [21].

Since, the objective of this paper is to present an efficient and effective method which provides better average retrieval efficiency with less computational time and cost, the approach selective relevance feedback is introduced to improve the performance of the system. The investigation is presented in this direction in the paper using F-norm based feature extraction of sub bands by complex wavelet transforms. The selective relevance feedback further enhances the performance of the system in terms of retrieval accuracy.

The paper is organized as follows. The theory related to dual tree complex wavelets & F-norm theory is discussed in section 2. The design and implementation of proposed algorithm is discussed in section 3. The experiments and its results are discussed in section 4 followed by conclusion in section 5.

2. WAVELET DECOMPOSITION

2.1 Dual tree complex wavelet transform

In multi resolution analysis of wavelets, two QMF (Quadrature Mirror Filter) pairs are used to generate low pass and high pass information. The low pass information consists of approximated version of high resolution image and the high pass gives sharper variation details. The dual tree complex wavelet transform uses two trees in parallel to generate the output interpreting them as real and imaginary part of complex coefficient. The QMF filter pairs generate the real and imaginary coefficients in the analysis branch. The dual tree complex transform decomposes the image into sub bands providing the two smoothed versions of image and the information in six different directions at each stage. All the filters used in the analysis are real & orthogonal [14, 16]. The output of the QMF filters is given as,

$$\Phi_1(x, y) = \Phi_h(x) \cdot \Phi_h(y) \quad \Phi_2(x, y) = \Phi_g(x) \cdot \Phi_g(y) \quad (1)$$

$$\Psi_{1,1}(x, y) = \Phi_h(x) \cdot \Psi_h(y) \quad \Psi_{2,1}(x, y) = \Phi_g(x) \cdot \Psi_g(y) \quad (2)$$

$$\Psi_{1,2}(x, y) = \Psi_h(x) \cdot \Phi_h(y) \quad \Psi_{2,2}(x, y) = \Psi_g(x) \cdot \Phi_g(y) \quad (3)$$

$$\Psi_{1,3}(x, y) = \Psi_h(x) \cdot \Psi_h(y) \quad \Psi_{2,3}(x, y) = \Psi_g(x) \cdot \Psi_g(y) \quad (4)$$

The resultant six wavelets generated using equations (2), (3) and (4) are as follows,

$$\Psi_i(x, y) = \Psi_{h,i}(x) + \Psi_{g,i}(y) \quad (5)$$

$$\Psi_{i+3}(x, y) = \Psi_{h,i}(x) + \Psi_{g,i}(y) \quad (6)$$

for $1 \leq i \leq 3$ are directional and two times redundant. These six wavelets are strongly oriented in $\{+15^\circ, +45^\circ, +75^\circ, -15^\circ, -45^\circ, -75^\circ\}$. These wavelets are strongly orientated to capture information in respective direction and are shift invariant.

2.2 F –norm theory

Low frequency component provide a low scale approximation of image and best describes the original image. It contains large coefficients with more energy. The two-dimensional wavelet transform of the image has most of the energy conserved in the upper left-hand corner of the transform and consists primarily of values that are zero or near zero in the remaining three-quarters of transform. The image features can be very well defined with F-norm theory for the decreased dimension of the image. Feature vectors for all the images in the database can be found using F-norm theory .Calculation of feature vector from F-norm theory [19] is done as follows.

Suppose A is N x N square matrix of coefficients of LL frequency channel, then A_i is its i^{th} order sub matrix is defined as,

$$A_i = \begin{bmatrix} a_{11} & \dots & a_{1i} \\ \dots & \dots & \dots \\ a_{i1} & \dots & a_{ii} \end{bmatrix} \quad (7)$$

Where $i = 1, 2, \dots, N$

The F-norm for A_i is given as,

$$\|A_i\|_F = \left[\sum_{k=1}^i \sum_{j=1}^i |a_{kj}|^2 \right]^{1/2} \quad (8)$$

The feature vector V_{AF} using F- norm is defined as,

$$V_{AF} = \{\|A_1\|_F, \|A_2\|_F, \dots, \|A_N\|_F\} \quad (9)$$

3. PROPOSED METHODOLOGY

3.1 Feature extraction

The DT-CWT algorithm is used for feature extraction. The decomposition is carried out up to eighth level using selesnick's first and higher stage low pass & high pass filters. The DT-CWT provides the filter coefficients by passing the image (2-D signal) through real & imaginary trees. The calculations of F-norm features are carried out for all the three color components. The F-norm features are calculated for LL sub band at each level for all the color components using equation (7), (8) and (9).

The resulting feature vector using these features is given by,

Feature vector of each color component =

$$\Delta V_{AF} = \{\Delta A_1, \Delta A_2, \Delta A_3, \dots, \Delta A_n\} \text{-----} (10)$$

Where $\Delta A_i = \|A_i\|_F - \|A_{i-1}\|_F$ and $\|A_i\|_F = 0$.

Total number of features = 3 x Feature Vector of each color component.

3.2 Similarity measure

In general, the accuracy of the retrieved results is directly proportional to the accuracy of the similarity measurement. A similarity (or distance) measure is a way of ordering the features from a specific query point.

Vector elements in the feature vector are represented by ΔA_i and ΔB_i . The similarity between two images is given by the following similarity criteria. Let ' α_i ' be the similarity between the elements of feature vector of image in the database ΔA_i and the query image ΔB_i and is calculated by the following equation.

$$\alpha_i = \frac{\min(\Delta A_i, \Delta B_i)}{\max(\Delta A_i, \Delta B_i)}, \Delta A_i \neq 0, \Delta B_i \neq 0$$

$$1 \quad \Delta A_i = \Delta B_i = 0$$

The final similarity value ' α ' is given as,

$$\alpha = \sum_{i=1}^n c_i \alpha_i \text{-----} (11)$$

Where ' c_i ' for the above equation is calculated using the following equation.

$$c_i = \frac{2i-1}{n^2} \text{-----} (12)$$

Where $i=1,2,\dots,n$.

Such that $\sum_{i=1}^n c_i = 1$.

Similarity between the two images lies in between $0 \leq \alpha \leq 1$.

3.3 Selective relevance feedback

The retrieval accuracy of each individual class can be further improved by relevance feedback. In the proposed algorithm, only those query images having retrieval accuracy less than the average retrieval accuracy of that particular class without relevance feedback are considered for training using relevance feedback to improve its retrieval accuracy. This not only decreases the computational cost and time, but also improves the retrieval accuracy. The selected images are processed using relevance feedback. In both the cases, ' α ' similarity criteria is used for similarity measure. The system will classify top 100 images into two clusters containing the images similar to query image and other containing the images non relevant with respect query image. Features of two clusters are averaged to generate clustered feature vectors. The existing feature vector without relevance feedback is modified to generate the new feature vector by adding the clustered feature vector of relevant images and subtracting the clustered feature vector of non-relevant images. This

procedure is repeated until the end user retrieves maximum relevant images. However, in the experiment, only five iterations are used to improve the retrieval accuracy of selected query images. The retrieval accuracy of trained query image is used to replace its existing value of average retrieval accuracy without relevance feedback.

4. RESULTS AND DISCUSSION

The experiment was conducted on Wang database consisting of 1000 images belonging to 10 different classes. Namely, People, beach, elephant, horse, food, monument, rose, dinosaur, bus and mountain. The features are extracted by decomposing the 2-D signal (image) up to eighth level using dual tree complex wavelet transform. The feature vector of the images in the database consists of F- norm values of the LL component up to eighth level. The feature vector of all the images is constructed. Each image in the database is taken as query image & its feature vector is generated. The similarity measure between the query image and the image in the database is executed using ' α ' similarity criteria as given in equation (11).

The pre processing involves resizing to [256, 256] and converting to Y, Cb, Cr domain. The feature vector is constructed for all images in the database. Each image in the database consists of 1530 features obtained by 3 color components. The similarity measure is executed using ' α ' similarity measure to calculate the retrieval accuracy of query image and the average retrieval accuracy of all the classes. The retrieval accuracy of query image and the average retrieval accuracy of class are calculated as,

$$\text{Retrieval Accuracy} = \frac{\text{No. of Relevant images Retrieved}}{\text{Total No. of Relevant Images}} \text{-----} (13)$$

$$\text{Average Retrieval Accuracy} = \frac{1}{n} \sum_{i=1}^n \text{Retrieval Accuracy} \text{-----} (14)$$

Where n =No. of images under consideration

The performance of the system is further improved by training the query images with poor retrieval accuracy of each of the class under selective relevance feedback.

The Selective Relevance Feedback is implemented for image retrieval with DT-CWT which captures information from the magnitude of complex wavelet transform using F-norm theory. The features are extracted from Y, Cb and Cr components. The number of images having poor retrieval accuracy considered for training with relevance feedback and the average retrieval accuracy achieved after training for 5 iterations is shown in Table 1. The average retrieval accuracy obtained using ' α ' similarity criteria as similarity measure for with and without Selective Relevance Feedback up to 5 iterations is tabulated in Table 2. It is observed that the average retrieval accuracy increases with every iteration. Table 3 indicates the percentage of improvement achieved by implementing proposed method on average retrieval without feedback.

Table 1. Average Retrieval Accuracy of Images selected for Selective Relevance Feedback

Class	I	Average Retrieval Accuracy				
		With Selective Relevance Feedback				
		Iter 1	Iter 2	Iter 3	Iter 4	Iter 5
People	37	12.29	14.54	16.21	16.99	17.27
Beach	40	9.57	11.20	12.40	13.02	13.51
Building	44	11.41	12.67	13.38	13.97	14.23
Bus	59	10.43	14.05	16.85	18.88	20.01
Dinosaur	31	30.22	30.31	30.37	30.37	30.38
Elephant	53	14.50	17.48	19.36	20.73	21.66
Rose	41	10.50	11.48	11.50	11.61	11.61
Horse	39	30.49	32.73	32.89	32.95	32.97
Mountain	44	17.44	20.54	21.82	22.56	22.96
Food	43	12.23	17.48	20.75	22.37	23.25

I= No. of Images considered for Selective Relevance Feedback

Table 2. Average Retrieval Accuracy of all the Classes without & with Selective Relevance Feedback

Class	Average Retrieval Accuracy					
	With out Feed back	With Selective Relevance Feedback				
		Iter 0	Iter1	Iter 2	Iter 3	Iter 4
People	34.87	39.42	41.67	43.34	44.12	44.40
Beach	28.17	31.03	32.66	33.86	34.48	34.97
Building	26.09	28.90	30.13	30.84	31.43	31.69
Bus	18.15	22.19	25.80	28.60	30.63	31.76
Dinosaur	96.47	97.65	97.74	97.80	97.80	97.81
Elephant	27.61	32.41	35.38	37.26	38.63	39.56
Rose	44.06	48.16	49.02	49.02	49.02	49.02

Horse	59.41	73.45	75.69	75.85	75.91	75.93
Mountain	37.66	43.71	46.81	48.09	48.83	49.23
Food	28.43	34.76	40.01	43.28	44.90	45.78

Table 3. Comparison of outputs without and with Selective Relevance Feedback

Sr. No.	Class	Average Retrieval Accuracy without Selective Relevance Feedback	Average retrieval accuracy With Selective relevance Feedback	Improvement in Average Retrieval Accuracy With Selective Relevance Feedback
1	People	34.87	44.40	9.53
2	Beach	28.17	34.97	6.8
3	Building	26.09	31.69	5.6
4	Bus	18.15	31.76	13.61
5	Dinosaur	96.47	97.81	1.34
6	Elephant	27.61	39.56	11.95
7	Rose	44.06	49.02	4.96
8	Horse	59.41	75.93	15.82
9	Mountain	37.66	49.23	11.57
10	Food	28.43	45.78	17.35

5. CONCLUSION

In this paper, the implementation of proposed method and its comparison with retrieval without relevance feedback is carried out. The result indicates that the average retrieval accuracy is improved with Selective Relevance Feedback. It is observed that average retrieval accuracy increases for most of the classes by more than 10% in 5 iterations. The improvement in average retrieval accuracy is less for dinosaur and rose class. The food class has maximum improvement. The retrieval accuracy increases with each iteration. As training is carried out for selected images in the database, the computational cost and time decreases and average retrieval accuracy improves.

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