Re-ranking of Images and Removing Duplicate Images

Sheetal Kamble

Pune University, Department of Computer PICT, Pune, India

Abstract: *Image re-ranking is one of the most efficient way by which you can improve the image search results and has been adopted by many search engines. Texture analysis is popular operation in CBIR. In this paper we have combined text based search along with CBIR and removing of duplicate images is done using pixel matching algorithm. Text based search is done using tags. CBIR is done using texture feature. We have used haar wavelet decomposition for color images'-mean clustering is used to form the cluster of images and similarity matching is done using F-norm theory. Experimental results reflect the importance of wavelets in CBIR .Our system improves the retrieval performance and better matches.*

Keywords: CBIR, Haar wavelet, Image Retrieval, Re-ranking, k-means Algorithm

1. Introduction

Most of the web search engines such as yahoo, Google, Bing use keywords for the query and the keywords depend on surrounding text for searching images. It is hard for any user to describe the visual content of image accurately so users suffer from ambiguity of query keywords. Text based search is done using tags and CBIR is done using texture feature Texture is powerful low-level feature for image search and retrieval applications. Texture analysis is fundamental to many applications such as automated visual inspection, biomedical image processing, CBIR and remote sensing. Much research work has been done on texture analysis for the last four decades. Despite these efforts, texture analysis is still considered an interesting but difficult problem of 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. So far, there is no unique definition for texture. Scientific definition of texture is given as," Texture is an attribute representing the spatial arrangement of the grey levels of the pixels in a region or image".

A key idea for wavelets is the concept of scale. Scaling deals with how wavelet represents a signal over a given frequency band. The discrete wavelet transform initially decomposes an image into one approximation image and three detail images. It filters the original image with complementary low-pass and high-pass filters in each dimension. The filtered images are down sampled at every other pixel producing four images of half the resolution of the original. Haar wavelet has advantage of being easy to understand and simple to compute. The objective of investigation is to extract wavelet based color texture features and to demonstrate robustness of the feature vector thus obtained for CBIR.

The rest of the paper contains different section in section 2 image decomposition using haar wavelet transform is described. Section 3 feature extraction and section 4 contains indexing and clustering. Section 5 describes experimental results and finally conclusion.

2. Image decomposition using Wavelet Transformation

We used haar wavelet approaches for color image decomposition. These resulting decomposition coefficients are employed to perform image feature extraction and similarity match by using F-norm theory. Wavelet transforms provide a multi-resolution approach to texture analysis and classification. The computation of the wavelet transforms of a two-dimensional signal involves recursive filtering and sub-sampling. At each level, the signal is decomposed into four frequency sub-bands, LL, LH, HL, and HH, where L denotes low frequency and H denotes high frequency.

LL	LH
HL	HH

Figure 1: Level 1 of 2D wavelet transform

Haar wavelet transform

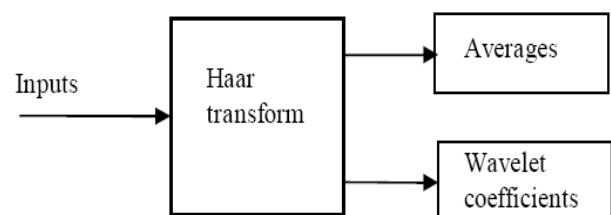**Figure 2:** Haar wavelet forward transforms

If a data set S0, S1 ….SN-1 contains N elements, there will be N/2 averages and N/2 wavelet coefficient values. The averages are stored in the upper half of the N element array and the coefficients are stored in the lower half. The averages become the input for the next step in the wavelet calculation, where for iteration i+1, $N_{i+1} = N_i/2$. The recursive iterations continue until a single average and a single coefficient are calculated. This replaces the original data set of N elements with an average, followed by a set of coefficients whose size is an increasing power of two.

The Haar equations to calculate an average a_i and a wavelet coefficient c_i from an odd and even element in the data set are:

$$a_i = \frac{s_i + s_{(i+1)}}{2} \qquad C_i = \frac{s_i - s_{(i+1)}}{2}$$

Steps for a 1D Haar transform of an array of N elements are as follows:

1. Find the average of each pair of elements using Equation 1. (N/2 averages)
2. Find the difference between each pair of elements and divide it by 2. (N/2 coefficients)
3. Fill the first half of the array with averages.
4. Fill the second half of the array with coefficients.
5. Repeat the process on an average part of the array until a single average and a single coefficient are calculated.

Steps for a 2D Haar transform are:

1. Compute 1D Haar wavelet decomposition of each row of the original pixel values.
2. Compute 1D Haar wavelet decomposition of each column of the row-transformed pixels.

Red, green and blue values are extracted from the images. Then we apply the 2D Haar transform to each color matrix.

Forward Haar transform for an eight element signal. Here signal is multiplied by the forward transform matrix. The arrow represents a split operation that reorders the result so that the average values are in the first half of the vector and the coefficients are in the second half. To complete the forward Haar transform there are two more steps. The next step would multiple the average values a_i by a 4x4 transform matrix, generating two new averages and two new coefficients which would replace the averages in the first step. The last step would multiply these new averages by a 2x2 matrix generating the final average and the final coefficient.

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{bmatrix} \Longleftarrow \begin{bmatrix} a_0 \\ c_0 \\ a_1 \\ c_1 \\ a_2 \\ c_2 \\ a_3 \\ c_3 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} & -\frac{1}{2} \end{bmatrix} \bullet \begin{bmatrix} s_0 \\ s_1 \\ s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_6 \\ s_7 \end{bmatrix}$$

Figure 3: Haar Forward ward transform for 8 element signal

3. Feature Extraction

Our System is based on wavelet decomposition of image in RGB color space. Decomposition is done offline. And after decomposition each resulting sub image is in fact a coefficient matrix.

Feature Vector

Suppose A is a square matrix and Ai is its ith order sub matrix where

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \cdots & \cdots & \cdots \\ a_{1n} & \cdots & a_{nn} \end{bmatrix}, \quad A_i = \begin{bmatrix} a_{11} & \cdots & a_{1i} \\ \cdots & \cdots & \cdots \\ a_{in} & \cdots & a_{ii} \end{bmatrix} \quad (i = 1 \sim n)$$

The F-norm of A_i is given as :

$$\left\| A_i \right\|_F = \left(\sum_{k=1}^{i} \sum_{l=1}^{i} \left| a_{kl} \right|^2 \right)^{1/2}$$

4. Indexing and clustering

We have used k-means algorithm for clustering and indexing of images. Euclidean distance is used for clustering of images. The k-means algorithm classifies the images into different groups. Clusters are made by calculating the distance and distance are arranged in ascending orders.

5. Experimental Results

A Database of more than 1000 images is taken. The images are of different classes (12). Like oranges, buses, dinosaurs, roses, horses, mountains, food, highways, sunflowers, daisy, sunset and oceans. There are 12 different group of images. First the images are retrieved based on text query and then by images. If the images are duplicate the images are removed.

Figure 4: Text based search

Paper ID: SUB156842

2643

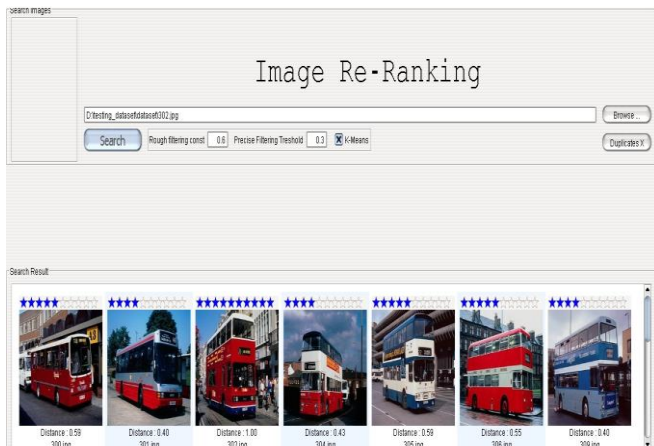After clicking on the red image the image path is taken an search is done.
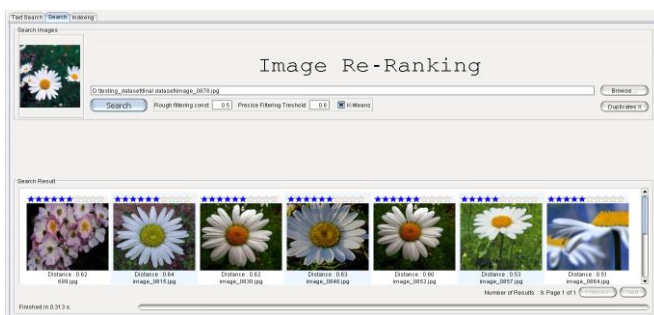

Figure 5: visual query Expansion.
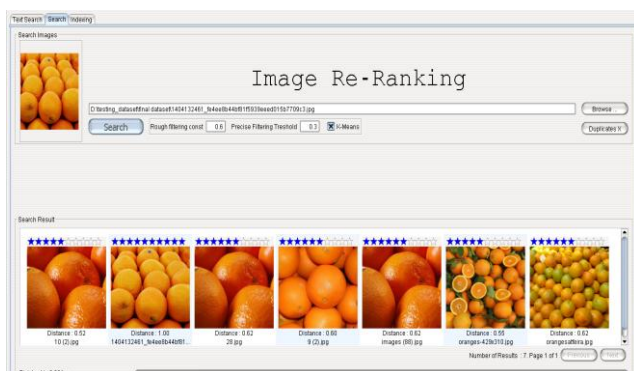

Figure 6: Image based search (daisy)

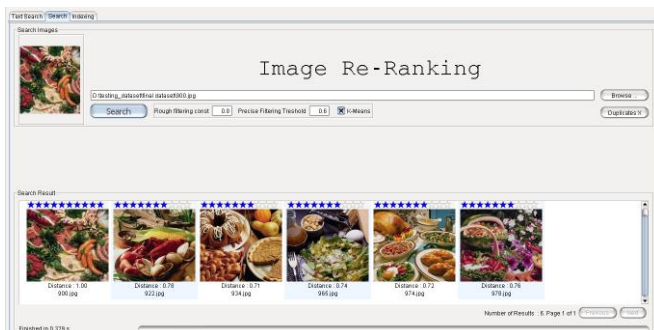**Figure 7:** Image based search (orange)

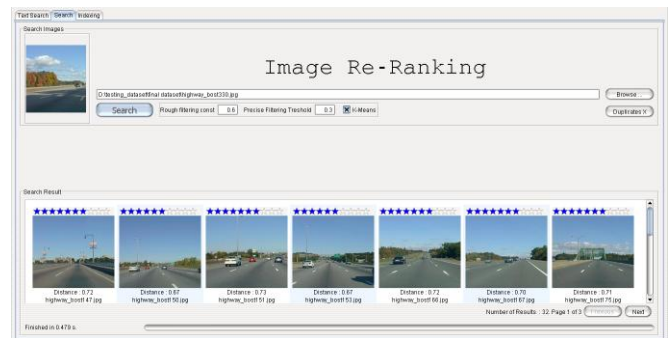
Figure 8: Image based search (food)

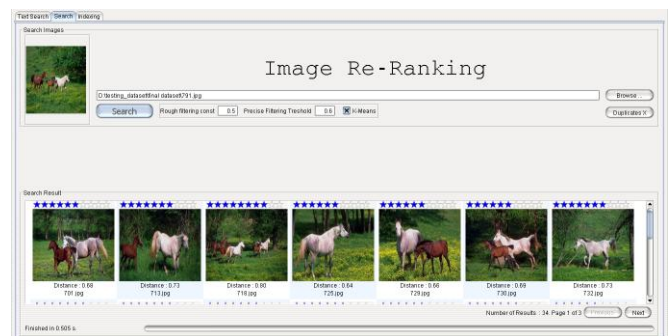**Figure 9:** Image based search (highway)

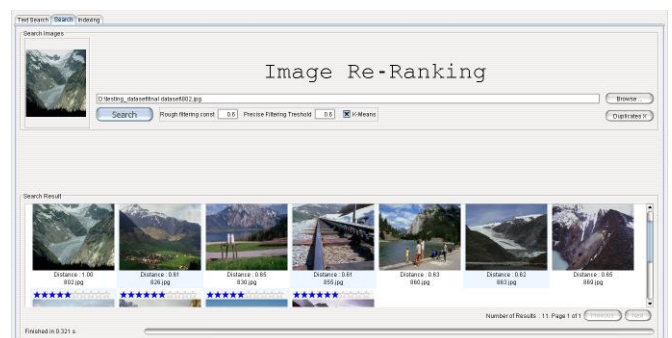**Figure 10:** Image based search (horse)

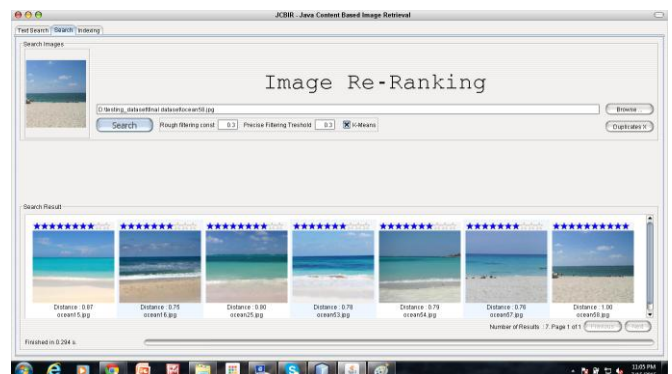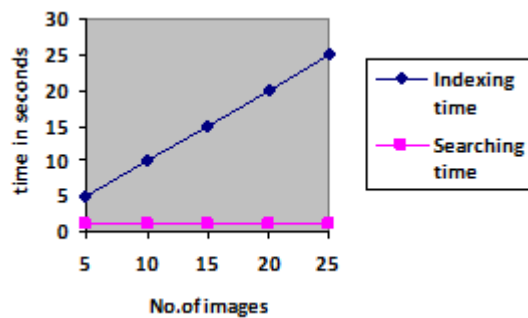**Figure 11:** Image based search (mountain)

Figure 12: Image based search (oceans)

4. Searching and Indexing Analysis

The graph shows the results of searching and indexing of dataset. It show that when number of images are increased in dataset the indexing time is greater. while searching of image takes less time as indexing is done first.

5. Conclusion

The proposed system use image retrieval first by tag based and then image based. Haar wavelet for wavelet decomposition of image is done. Clustering of images is done using k-means clustering .we found that performance of the system is improved and image ranking is done in better manner. Since retrieving of images from dataset is still difficult. In future we can work on the system to get better performance

References

[1] Xiaogang Wang; Shi Qiu; Ke Liu; Xiaoou Tang, "Web Image Re-Ranking Using Query-Specific Semantic Signatures," *Pattern Analysis and Machine Intelligence, IEEE Transactions on* , vol.36, no.4, pp.810,823, April 2014

[2] Yuxin Chen; Sampathkumar, H.; Bo Luo; Xue-wen Chen, "iLike: Bridging the Semantic Gap in Vertical Image Search by Integrating Text and Visual Features," *Knowledge and Data Engineering, IEEE Transactions on* , vol.25, no.10, pp.2257,2270, Oct. 2013

[3] Xiaoou Tang; Ke Liu; Jingyu Cui; Fang Wen; Xiaogang Wang, "IntentSearch: Capturing User Intention for One-Click Internet Image Search," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol.34, no.7, pp.1342,1353, July 2012

[4] Jun Huang; Xiaokang Yang; Xiangzhong Fang; Weiyao Lin; Rui Zhang, "Integrating Visual Saliency and Consistency for Re-Ranking Image Search Results," *Multimedia, IEEE Transactions on* , vol.13, no.4, pp.653,661, Aug. 2011

[5] Rasiwasia, N.; Moreno, P.J.; Vasconcelos, N., "Bridging the Gap: Query by Semantic Example," *Multimedia, IEEE Transactions on* , vol.9, no.5, pp.923,938, Aug. 2007

[6] Yushi Jing; Baluja, S., "VisualRank: Applying PageRank to Large-Scale Image Search," *Pattern Analysis and Machine Intelligence, IEEE Transactions on* , vol.30, no.11, pp.1877,1890, Nov. 2008

[7] Lixin Duan; Wen Li; Tsang, I.W.; Dong Xu, "Improving Web Image Search by Bag-Based Reranking," *Image Processing, IEEE Transactions on* , vol.20, no.11, pp.3280,3290, Nov. 2011

[8] Xinmei Tian; Dacheng Tao; Xian-Sheng Hua; Xiuqing Wu, "Active Reranking for Web Image Search," *Image Processing, IEEE Transactions on* , vol.19, no.3, pp.805,820, March 2010

[9] Yichen Yang; Hanjalic, A., "Prototype-Based Image Search Reranking," *Multimedia, IEEE Transactions on* , vol.14, no.3, pp.871,882, June 2012

[10] Afifi, A.J.; Ashour, W.M., "Content-Based Image Retrieval Using Invariant Color and Texture Features," *Digital Image Computing Techniques and Applications (DICTA), 2012 International Conference on* , vol., no., pp.1,6, 3-5 Dec. 2012

[11] Bin Wang; Zhiwei Li; Mingjing Li; Wei-Ying Ma, "Large-Scale Duplicate Detection for Web Image Search," *Multimedia and Expo, 2006 IEEE International Conference on* , vol., no., pp.353,356, 9-12 July 2006

[12] http://wang.ist.psu.edu/

[13] Verma, D.N.; Maru, V.; Bharti, "An efficient approach for Color Image Retrieval using Haar wavelet," *Methods and Models in Computer Science, 2009. ICM2CS 2009. Proceeding of International Conference on* , vol., no., pp.1,5, 14-15 Dec. 2009

[14] Siddiquie, B.; Feris, R.S.; Davis, L.S., "Image ranking and retrieval based on multi-attribute queries," *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on* , vol., no., pp.801,808, 20-25 June 2011

Paper ID: SUB156842

2645