Texture Image Retrieval Using Greedy Method

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Abstract. There is a huge amount of methods for extracting image descriptors and defining the similarity measures. In this paper, we try to improve texture image retrieval performance with post processing based on the greedy technique called Prims algorithm. In the proposed method feature database is represented using distance matrix, which is the distance between every image of the database. Due to symmetric property of a matrix, we can improve the efficiency and effectiveness of the proposed retrieval system. However for large database the size of the matrix is large. The proposed system is tested with three different image descriptors, namely combined rotated complex wavelet filters (RCWF) and dual tree complex wavelets (DT-CWT), Contourlet Transform (CT), and Discrete Wavelet Transforms (DWT).

1 Introduction

Due to drastic growth of multimedia and digital technology in recent years, there is a need of effective and efficient management of digital image libraries and other multimedia databases. Hence, storage and retrieval of images in such libraries become a real demand in industrial, medical, crime prevention, biometric systems, and other applications. Content-Based Image Indexing and Retrieval (CBIR) is considered as a solution. In such systems, important features are extracted from every picture and stored as a feature vector. Content-based image retrieval has attracted substantial interests in the last decade [1,5,8,9,10]. Generally image retrieval system can be divided in to two different steps. First image descriptors have to be extracted by analyzing color, texture, shape or context. Second a similarity measure analyzing variations in images features has to be defined**.** Then given a query image, all other images of the database are sorted based on their similarity rank to the query image. Finally, high ranking images are returned to the users.

There are several methods available to perform these two steps in Content-based image retrieval. Recently some effort was also put on post-processing by using the obtained similarities between all given images [11]. In this paper, for post processing step we used greedy algorithm called Prims. Using this algorithm we can find minimum cost spanning tree.

1.1 Related Work

In 2004, Zhou et al. [12,13,14] proposed a novel semi-supervised learning algorithm named manifold-ranking. In this algorithm, a connected graph is created first, in

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which vertex represents the data and edge represents the similarity between vertices, and then the score diffuses from the vertices to their neighbors. After several rounds, all the vertices get stable scores. Finally, all the data point are ranked by the scores of the corresponding vertices in the graph. The assumption of the algorithm is that all the data points are distributed in a low dimension manifold, which is embedded in the high dimension features space. Compared to the pairwise method, the main difference of the manifold ranking based method is, it ranks all the data according to the manifold structures represented by the labeled and unlabeled data, which means that the algorithm ranks the data by considering local and global consistency simultaneously. In [3,4], a pair wise graph based manifold ranking algorithm [12] is adopted to build image retrieval. These graph based methods motivates us to do work on the image retrieval using greedy algorithm.

The main contribution of this paper is summarized as, we have proposed novel texture image retrieval using greedy method called Prims algorithm. The experimental results of proposed method perform better compared with earlier approach. The rest of paper is organized as follows. In section 2, we discuss the image descriptors in brief. In section 3, we discuss the proposed greedy algorithm for image retrieval. In section 4, the experimental results are given and finally section 5 concludes the work.

2 Image Descriptors

For image feature extraction we have used three different methods, namely combined rotated complex wavelet filters (RCWF) and dual tree complex wavelets (DT-CWT), Contourlet Transform (CT), and Discrete Wavelet Transforms (DWT). DT-CWT, DT-RCWF, and CT are explained below in short.

2.1 DT-CWT

Real DWT has poor directional selectivity and it lacks shift invariance. Drawbacks of the DWT are overcome by the complex wavelet transform (CWT) by introducing limited redundancy into the transform. But still it suffer from problem like no perfect reconstruction is possible using CWT decomposition beyond level 1, when input to each level becomes complex. To overcome this, Kingsbury [7] proposed a new transform, which provides perfect reconstruction along with providing the other advantages of complex wavelet, which is DT-CWT. The DT-CWT uses a dual tree of real part of wavelet transform instead using complex coefficients. This introduces a limited amount of redundancy and provides perfect reconstruction along with providing the other advantages of complex wavelets. The DT-CWT is implemented using separable transforms and by combining subband signals appropriately. Even though it is non-separable yet it inherits the computational efficiency of separable transforms. A complex valued $\psi(t)$ can be obtained as

$$\psi(x) = \psi_h(x) + j\,\psi_g(x) \tag{1}$$

where $\psi_h(x)$ and $\psi_g(x)$ are both real valued wavelets.

2.2 DT-RCWF

Recently, Kokare et.al.[6] have designed 2D- rotated complex wavelet transform. Directional 2D RCWF are obtained by rotating the 2D DT-CWT filters by 45^0 so that decomposition is performed along new direction, which is 45^0apart from decomposition of DT-CWT. The size of a newly obtained filter is $(2N-1)X(2N-1)$, where N is the length of the 1-D filter. The decomposition of input image with 2-D DT-RCWF followed by 2-D downsampling operation is performed up to the desired level. The computational complexity associated with DT-RCWF decomposition is the same as that of standard 2-D DT-CWT, if both are implemented in the frequency domain. The set of DT-RCWFs retains the orthogonality property. The six subbands of 2D DT-RCWF gives information strongly oriented at ($30^\circ, 0^\circ, -30^\circ, 60^\circ, 90^\circ, 120^\circ$).The mechanism of the DT-RCWF is explained in detail in [6]. The 2D DT-CWT and RCWF provide us more directional selectivity in the directions $\begin{Bmatrix} \left(+15^\circ,\ +45^\circ,\ +75^\circ,\ -15^\circ,\ -45^\circ, -75^\circ\right), \\ \left(0^\circ, +30^\circ,\ +60^\circ,\ +90^\circ,\ 120^\circ,\ -30^\circ\right) \end{Bmatrix}$.

2.3 Contourlet Transform

Multiscale and time frequency localization of an image is offered by wavelets. But, wavelets are not effective in representing the images with smooth contours in different directions. The Contourlet provides a much richer set of directions and shapes. Hence they are more effective in capturing smooth contours and geometric structures in images [2]. Contourlet transform is a multiscale and directional image representation that uses first a wavelet like structure for edge detection, and then a local directional transform for contour segment detection.

3 Proposed Greedy Algorithm

In this paper, we proposed the new content-based image retrieval using Prims algorithm. Prim's algorithm is a greedy algorithm that finds a minimum cost spanning tree for a connected weighted undirected graph. So we represented the feature database in the form of distance matrix. Due to symmetric matrix, we considered only upper main diagonal elements in order to retrieve the images. The size of matrix is large for large image database. The proposed method is tested using the different image descriptors namely combined dual tree rotated complex wavelet filters(DT-RCWF) and dual tree complex wavelet transform(DT-CWT)[6], Contourlet Transform(CT)[2], and Discrete Wavelet Transform(DWT)[6] separately.

Let $G = (V, E)$ be connected weighted undirected graph, V is the set of vertices represents images and E is the set of edges, which represent the similarity between images Cabrera distance d_{ij} between the image i and j represents the weight of each edge. Fig. 2 shows sample example for the connected weighted undirected graph, and its minimum cost spanning tree.

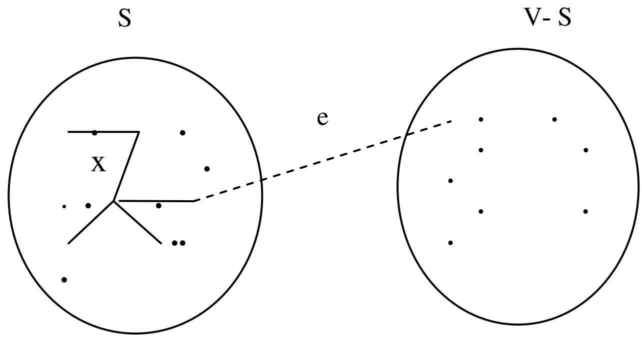
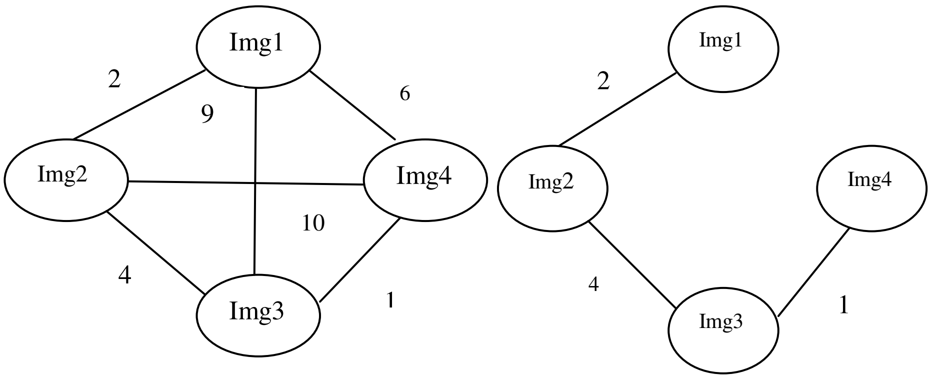


Fig. 1. Prim's algorithm: the edges X form a tree, and S consists of its vertices



a) Sample graph example **b) its minimum cost spanning tree**

Fig. 2. Sample graph and its spanning tree

Fig 1 shows, the algorithm continuously increases the size of a tree, one edge at a time, starting with a tree consisting of a single vertex (query image q), until it spans all vertices (all images). An algorithm 1 describes the proposed method.

Algorithm 1: Greedy Algorithm for Image Retrieval

Input: Image Database DB, Query image q, distance matrix

Output: Retrieved Images
Begin
1 $V_T = \{q\}$
2 $E_T = \emptyset$
3 $i = 1$

4 While $i \le |V| - 1$ do
5 Begin
6 Find a minimum distance edge $e^* = (v^*, u^*)$ among all the edges
7 Such that v is in V_T and u is in $V - V_T$
8 $V_T = V_T \cup \{u^*\}$
9 $E_T = E_T \cup e^*$
10 End
11 Sort the edges in E_T
12 Display first Top N images
End

A query is considered as the starting vertex in the Prims algortim(line 1). In every iteration algorithm finds minimum distance edge $e^* = (v^*, u^*)$ among all the edges such that v is in V_T and u is in $V - V_T$ (line 6 and 7) and then that vertex(image) u^* and edge e^* is added to the minimum cost spanning tree vertices set V_T and set of edges E_T respectively(line 8 and 9). This procedure is repeated by number of images (vertices) minus one time(line 4 to line 10) . Finally tree edges are sorted and top most N similar images displayed (line 11 and 12). Fig 2 shows the formation of minimum cost tree.

A simple implementation using an adjacency matrix graph representation and searching an array of weights to find the minimum weight edge to add requires $O(|V^2|)$running time. Using a simple binary heap data structure and an adjacency list representation, Prim's algorithm can be shown to run in time$O(E \log V)$, where $|E|$ is the number of edges and $|V|$ is the number of vertices.

4 Experimental Results

To test the efficiency of proposed graph based CBIR, we employed the Brodatz texture database [6]. It consists of 116 different textures. We used 108 textures from Brodatz texture photographic album, seven textures from USC database and one artificial texture. Size of each texture image is 512×512. Each 512×512 image is divided into sixteen 128×128 non overlapping subimages, thus creating a database of 1856 texture images. We used combined dual tree rotated complex wavelet filters (DT-RCWF) and dual tree complex wavelet transform (DT-CWT)[6], Contourlet Transform(CT)[2], and Discrete Wavelet Transform(DWT)[11] to extract image features separately.

For each experiment, one image was selected at random as the query image from each category and thus retrieved images were obtained. For performance evaluation of the image retrieval system, it is significant to define a suitable metric. We employed accuracy, which is defined as follows

$$Accuracy = \frac{Number\ of\ relevant\ images\ retrieved}{Number\ of\ relevant\ images\ in\ database} \quad (2)$$

The comparative retrieval performance of the proposed system is shown in Table 1. Fig. 3 shows the comparison results for image retrieval using different image descriptors and improvement of performance with proposed method.

Table 1. Percentage Average Retrieval Accuracy for Brodatz texture Database

Image descriptors	%Average retrieval accuracy of earlier methods	%Average retrieval accuracy of proposed method
DWT[11]	69.61	72.31
CT[12]	76.13	78.61
DT-CWT+DT-RCWF[11]	78.5	81.61

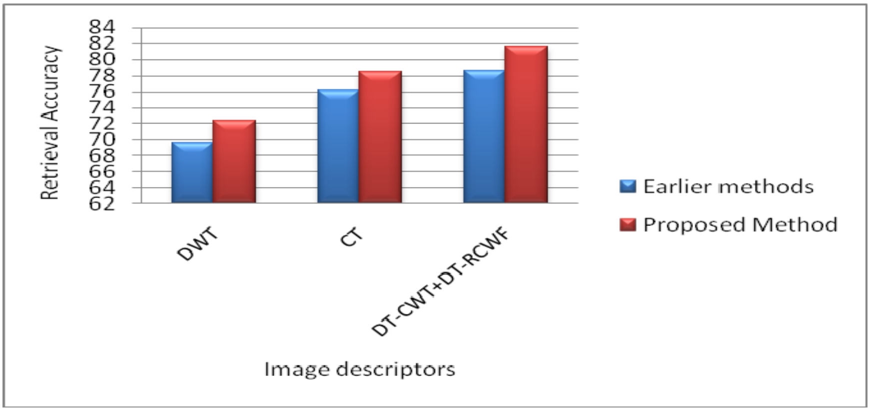


Fig. 3. Retrieval performance

5 Conclusions

In this paper, we have introduced a novel Content-Based Image Retrieval framework based on greedy technique, which uses the connected undirected weighted graph structure. It is used to represent the relationship among the vertices (images). We have tested proposed system using three different texture features. Experimental results indicate that the proposed method using combined DT-CWT and DT-RCWF features retrieval rate increases from 78.5% to 81.61%, from 76.13% to 78.61% using CT features and 69.61% to 72.31% on texture database. Hence experimental results of the proposed method are satisfactory compared to the existing methods.

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