An Enhanced Image Retrieval using Contribution-based Clustering Algorithm with Spatial Feature of Texture Primitive and Edge Detection

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ABSTRACT
An image retrieval based on content has been a very effective research area, with various techniques developed by various researchers. Developing those techniques needs proficiency in various areas of information technology: databases and indexing structures, system design and integration, graphical user interfaces (GUI), signal processing and analysis, man-machine interaction, user psychology, etc. This paper focuses on using Spatial Feature of Texture primitive and edge detection by using contribution based clustering algorithm and its efficiency is measured by comparing it with color feature. Experimental results show that the proposed method has increased the cost of precision of image retrieval.

Keywords: Texture primitive, Edge detection, Contribution based clustering algorithm.

1. INTRODUCTION
The technique of content-based retrieval from image repository has turns out to be a significant research field in computer vision and image processing. In general, CBIR intends to build methods that support effective searching and browsing of large image digital libraries with the help of obtaining the features from the image. This paper focuses on using Spatial Feature of Texture primitive and edge detection by using contribution based clustering. Clustering is a method of unsupervised classification, where data points are grouped into clusters based on their similarity. Clustering algorithms can be broadly classified into five types: Partitional clustering, Hierarchical clustering, Density-based clustering, Grid-based clustering and Model-based clustering. The new algorithm of contribution based clustering algorithm comes under the category of Partitional clustering. The block diagram of CBIR is shown Fig1. According to the examinations of the statistical distribution of the texture primitive, the spatial distribution map of every characteristic is proposed to illustrate the image texture information. Texture is the pattern of information or arrangement of the structure found in a picture.

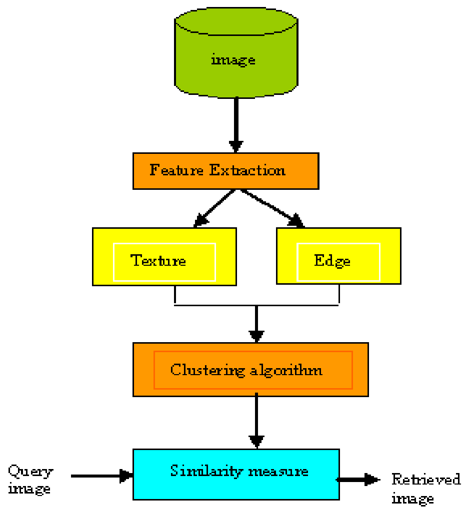


Figure 1: Block diagram of CBIR

Texture uses features in the examination and interpretation of images. It can be features as a set of local statistical properties of the pixel gray level intensity.

Texture is one of the significant features in detecting objects or regions of interest in an image. There are two kinds of texture according to the spatial frequency, such as fine and coarse. Fine textures have high spatial frequencies or a large number of edges per unit area. Coarse textures have low spatial frequencies or a small number of edges per unit area. Canny edge detection algorithm is used to acquire the edge features. some steps involves in this algorithm such as Smoothing, Finding Gradients, Non-Maximal Suppression, Edge Threshold, Thinning. After gathering the texture primitive features and edge features, both are combined and according to the similarity measures, the images are retrieved.

The rest of the paper is organized as follows. Section 2 describes related works Section 3 describes Methodology, section 4 describes contribution based clustering algorithm, section 5 describes Experimental results. Conclusion and future scope of research in section 6.

2. RELATED WORKS
A content-based image retrieval system has been done using clustering technique [1] in many applications such as academia, hospital, commerce etc. CBIR works on extracting stored images from a collection by comparing features automatically extracted from the images. The features utilized are mathematical determining of texture, edge, shape etc.

P. Sankara Rao.et. al [2], proposed a neural network for content based image retrieval. The author first performs the clustering of the images available in the database using hierarchical and k- mean clustering. This clusters obtained is then supplied to the neural network which uses radial basis function to derive the relevant images supplied through user query.

Tapas Kanungo, David M. Mount, Nathan S. Netanyahu, Christine D. Piatko, Ruth Silverman, and Angela Y. Wu [3], proposed an enhanced Lloyd's algorithm which is simple to implement and compute and gives better results as compared to other k- mean heuristics available which are NP hard.

Chang Wen Chen, Jiebo Luo and Kevin J. Parker[4], discusses the problem faced while using K- mean algorithm and propose adaptive k- mean algorithm, its working and advantage over simple K- mean. Weiling Cai, Songcan Chen, Daoqiang Zhang[5], discusses the fuzzy C- mean clustering its working and drawbacks. The paper propose that incorporating the local information in the objective function while clustering improve the performance of the algorithm and make it resistant to noise and outliers.

Ritu Shrivastava et.al [6], proposed to compare the two clustering techniques: K- mean and C-mean clustering for image retrieval. Clustering groups similar images based on some properties for efficient and faster retrieval**.** The analysis shows that both techniques works on the distance metric concept, that is both computes the distance between the centroid of the cluster and seed point. The one with the minimum distance is taken into account and is added to the cluster. Both algorithm uses prior identified number K (number of clusters to be formed) therefore the results depends on the cluster number K and initial choices of seed points. K- mean algorithm is easy and fast to compute on the other hand C- mean algorithm takes long computational time. Both converges but suffers from the problem of local minimum.

E.Vamsidhar et.al [7], suggest the clustering as two stages such as hierarchical clustering and RBFN network. First, they First, they going to filter most of the images in the hierarchical clustering and then apply the clustered images to RBFN network. where images are initially clustered into groups having similar color content and then the preferred group is clustered using Hierarchical clustering which assists for faster image retrieval and also allows the search for most relevant images in large image databases. RBFN Network is a multi layer neural network approach which uses K-Means clustering and Gaussian function to retrieve the similar images by comparing the images in the databases and query images.

P.S. Hiremath and Jagadeesh Pujari [8] proposed a novel method for image retrieval using texture within a multiresolution multigrid framework. The images are partitioned into non-overlapping tiles. Texture feature are extracted from these tiles at two different resolutions in two grid framework. Feature is drawn from conditional co-occurrence histograms computed by using image. An integrated matching scheme based on most significant highest priority (MSHP) principle and adjacency matrix of a bipartite graph constructed between image tiles, is implemented for image similarity.

3. METHODOLOGY

3.1 Texture Primitive

Supposed I is a $M \times N$ image. The image is divided into $m\times m$ pixel non-overlap blocks. For each block, the mean value μ and the standard deviation σ of gray in an image block is calculated according to

$$\mu = \frac{\sum_{\forall i,j} p(i,j)}{4} \quad \textbf{(1)}$$

$$\sigma = \frac{\sum_{\forall i,j} \| p(i,j) - \mu \|}{4} \quad \textbf{(2)}$$

where **p(x, y)** is the gray value of the pixel located in **(x, y)** for image **I** . By the principle of BTC, for those pixels in each block whose gray value is bigger than **μ**, we make them equal to **"1"**, otherwise, **"0".** In this way, a series of binary blocks are gained. It is evident that those binary blocks can embody the texture feature for image blocks. In this experiment, to see that similar texture structure leads to the similar binary blocks. So, define these binary blocks as texture primitive and make use of the decimal value corresponding to binary value to express the texture primitive. In this paper, a threshold **β** is adopted. Those image blocks whose standard deviation is smaller than **β** are regard as even blocks and make the primitive value as **"0".** In this experiment, we adopted the statistical method called statistical distribution of texture primitive.

3.2 The spatial feature of the texture primitive

After defining the texture primitive, an image of **M xN** is corresponding to a matrix of [**M /m] x [N / m]** expressed by **P . P (x, y)** is the index of the texture primitive which is located in **(x, y)** in ***P*** . To extract the spatial information of the texture primitive, for certain kind of texture primitive in **P (x, y)** , we kept its value and make others equal to zero. The spatial distribution map of texture primitive is constructed. Based on the map, the spatial feature is proposed

$$A_i = \{(x,y) \mid (x,y) \in P, P(x,y) = i, 0 \le i \le 2^{m\times m} - 1\}$$

.

It defines the set of points with index **i** in **P** and |**Ai|** be the number of elements in A_i . Let **Ci=(Xi,Yi)**be the centroid. Moreover, **Xi**and **Yi** are calculated as

$$x_i = \frac{1}{|A_i|} \sum_{(x,y)\in A_i} x; \quad y_i = \frac{1}{|A_i|} \sum_{(x,y)\in A_i} y \quad \textbf{(3)}$$

Let r_i be the radius of the point whose index is **i.** The definition is shown by

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad \textbf{(4)}$$

Therefore, the sum of the distance between all points whose index is **i** and centroid is defined as follow

$$R_i = \sum r_i = \sum_{(x,y)\in A_i} \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad \textbf{(5)}$$

c)Canny Edge Detection Algorithm

The edge information in the image is obtained by using the canny edge detection. It involves five steps such that

Step 1: Smoothing*:* Smooth the image with a two dimensional Gaussian. In most cases the computation of a two dimensional Gaussian is costly, so it is approximated by two one dimensional Gaussians. The kernel of a Gaussian filter with a standard deviation of σ = 1.4 is shown in Equation

$$B = \frac{1}{159}\begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} \qquad \textbf{(6)}$$

Step 2: Finding Gradients*:* Take the gradient of the image this shows changes in intensity, which indicates the presence of edges. This actually gives two results, the gradient in the x direction and the gradient in the y direction.

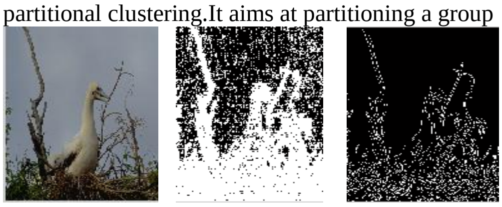
$$K_{GX} = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & -2 & -1 \end{bmatrix}$$

$$K_{GY} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad \textbf{(7)}$$

Step 3: Non-Maximal Suppression: Edges will occur at points where the gradient is at a maximum. The magnitude and direction of the gradient is computed at each pixel.
Step 4: Edge Threshold*:* The method of threshold used by the Canny Edge Detector is referred to as "hysteresis". It makes use of both a high threshold and a low threshold.
Step 5: Thinning*:* Using interpolation to find the pixels where the norms of gradient are local maximum.
The combination of texture primitive and edge feature is shown Figure 2

4. CONTRIBUTION BASED CLUSTERING ALGORITHM

Contribution based clustering is under the category of partitional clustering.It aims at partitioning a group



(a) (b) (c)

Figure 2: (a)Query image (b) Related Texture Primitive (c) Related Edge Feature.

of data points into disjoint clusters [9].In this paper the images is partitioned into a number of clusters. given a query images , the system retrieves all images from the cluster ie) closest in content to the query image.

Algorithm

Contribution based clustering algorithm optimizes on two measures, namely the intra-cluster dispersion and inter-cluster dispersion.

Intra-cluster dispersion

$$\alpha = \frac{1}{n}\sum_{x \in C_i}(\boldsymbol{x} - \boldsymbol{m}_i)^2$$

Inter-cluster dispersion.

$$\beta = \frac{1}{k}\sum_{i=1}^{k}(\boldsymbol{m}_i - \bar{\boldsymbol{m}})^2$$

where **k** is the number of clusters and **m** is the mean of all centroid. The algorithm tries to minimize α and maximize**β.**

Step 1: Initialization
Randomly select k centroids ($\boldsymbol{m}_1, \boldsymbol{m}_2, \ldots, \boldsymbol{m}_k$)
For each point x
  Find $1 \le l \le k$ such that distance(x, m_l) is minimum
  Add x to cluster C_l and update centroid m_l.
End For

Step 2: Negative Contribution Points
For each cluster C_l
  For each point $\boldsymbol{x} \in C_l$
    If contribution($\boldsymbol{x}$, C_l) < 0
      Move x to a cluster C_p such that contribution ($\boldsymbol{x}$,C_p) is maximum
      Update centroid $\boldsymbol{m}_p$
    End If
  End For
End For

Step 3: Positive Contribution Points
For each cluster C_l
  For each point $\boldsymbol{x} \in C_l$
    If contribution($\boldsymbol{x}$, C_l) ≥ 0
      Move $\boldsymbol{x}$ to a cluster C_p such that $\frac{\alpha - \alpha_{new}}{\alpha} + \frac{\beta_{new} - \beta}{\beta_{new}}$ is maximum
      Update centroid $\mathbf{m}_p$
    End if
  End for
End for

$\alpha_{\mathbf{new}}$ and $\beta_{\mathbf{new}}$ are values of α and β after the point **x** is moved to cluster $\mathbf{c_p}$.
A cluster C_i with n points and centroid m_i, the average intra-cluster dispersion is given by

$$dispersion(C_i) = \frac{1}{n}\sum_{x \in C_i}(\boldsymbol{x} - \boldsymbol{m}_i)^2$$

The contribution of a point $x \varepsilon c_i$ is calculated as
Dispersion (C_i)=dispersion(C_i-{x})-dispersion(C_i).

In this paper-clustering algorithm that treats points with negative contribution different from positive contribution. In negative contribution, the point is shifted to a cluster. Where contribution is highest, possibly positive. In other hand ,for positive contribution to optimize both the intra-cluster and inter-cluster.

5. EXPERIMENTAL RESULTS

This experiment is performed on the database which consists of 777 images. The test database consisted of 109 images belonging to 18 categories. Its obtained from Concept Recognition for CBIR research project image dataset [10].All images includes natural scenes, plants, animals, landscapes etc. Then, the retrieval accuracy is measured in terms of precision. The retrieval images are shown in Figure 3.

The precision represents the ratio of number of images in retrieved images relevant to the query to the number of retrieved images. The cost of precision is shown in Table 1 and Figure 4.

$$\text{Precision} = \frac{\text{Number of relevant images Selected}}{\text{Total number of retrieved images}}$$

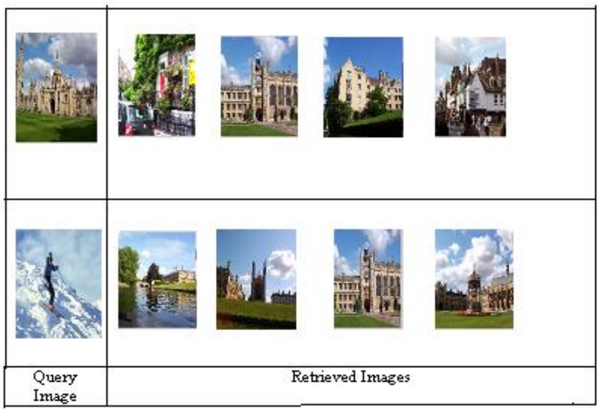


Figure 3: Query with Retrieved Images

Table 1: Cost of Precision in Color and Texture Primitive with Edge Feature

[3] Tapas Kanungo, David M. Mount, Nathan S.Netanyahu, Image	Cost of Precision	
	Color	Texture Primitive with Edge
1	0.7	0.8
2	0.7	0.9
3	0.6	0.8
4	0.7	0.8
5	0.8	0.9
6	0.7	0.9

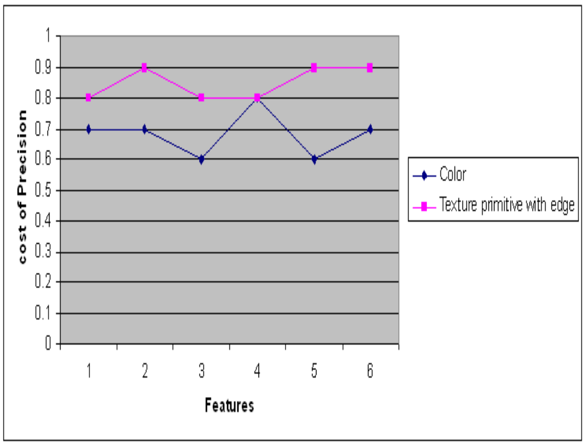


Figure 4: Comparison of Color and Texture Primitive with Edge Feature

6. CONCLUTION AND FUTURE SCOPE

This experiment classifies the images by using contribution based clustering algorithm by extracting texture primitive and edge. The experimental results suggest that the proposed image retrieval technique results in the increased cost of precision when compared to existing approach using color feature. In future more efficient features such as shape, region, color can be incorporated for better results or some other clustering technique can be used to obtain higher precision of image retrieval.

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