ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 3, March 2017

Analysis of Clustering Techniques for Retrieval of Images using Proposed Feature Extraction Method

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ABSTRACT: The purpose of this paper is retrieval of images from the image database using clustering algorithms. It uses the novel approach of feature extraction technique which is based on combination of SIFT descriptor, color histogram and texture features. The extracted features are then clustered applying different clustering algorithms and the clusters are used to retrieve relevant images to the query image. In this work, Corel-1k database is used. This work presents a comparative analysis of various feature extraction techniques with various clustering algorithms for image retrieval. The experimental results of this work shows performance of various clustering algorithms.

KEYWORDS: SIFT, histogram, texture features, clustering algorithms

I. INTRODUCTION

In recent times, the rapid growth of high dimensional data, the deployment of huge image databases supporting a wide range of applications has now become achievable. Databases have a great potential in attracting more users in different fields like environmental, design, marketing, medicine, arts and publishing. Accessing the required and relevant images from large image databases in an efficient manner is now a great necessity.

Image retrieval is the fast growing and challenging research area with regard to digital images. Retrieval focuses at developing new techniques that support effective searching and browsing of large digital image libraries based on derived image features. Feature extraction involves reducing the amount of resources required to describe a large set of data. Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the retrieval can be performed by using this subset instead of the complete data. Meanwhile, the next important phase today is focused on clustering techniques. Clustering algorithms can offer superior association of multidimensional data for accurate retrieval. Clustering algorithms allow a nearby neighbour search to be efficiently performed. Hence, the image mining is rapidly gaining attention among the researchers in the field of data mining, information retrieval and multimedia databases. The main goal is to mine the images from the social media by extracting the features of the images using various descriptors from the image database and then display the results according to the human expectations based on several clustering algorithms.

II. RELATED WORK

Sonal Geol, et al. (2016) proposed an open source intelligent real time image search system to retrieve the images and presented comparison between different features and convolutional neural network model to retrieve similar images. Hasan Mahmud, et al. (2016) presented a hand gesture recognition system using SIFT features, they applied the SIFT features on binary images and keypoints from the images are used in k-means clustering to reduce the feature dimensions. Jerrin Varghese (2015) studied image search based on scale invariant feature transform descriptors using k-means clustering algorithm. N. Puviarasan, et al. (2014) proposes a combined shape and texture feature extraction technique for content based image retrieval system. Aiysha Begam, et al. (2013) proposes a CBIR system exploitation the local color and texture options of chosen image sub-blocks and world color and form options of the image. A combined color and texture feature is computed for every region. Hiran Ganegedara, et al. (2012) proposed Parallel GSOM algorithm has demonstrated that parallel computation can significantly reduce training time for self-organizing maps. Hsin-Chien Huang, et al. (2012) proposed an affinity aggregation spectral clustering algorithm ring, SIFT, spectral clustering. For aggregating affinity matrices for spectral clustering, it was more immune to ineffective affinities and irrelevant features. Also, it enables the construction of similarity measures for clustering less crucial. Nenad Tomašev, et al. (2011) explores the ways to represent images as bags of SIFT feature clusters and created a hybrid clustering algorithm which offers more flexibility than simple spatial k-means clustering. N.Nanthini, et al. (2017) proposed a combination of histogram and SIFT feature extraction technique with spectral clustering algorithm to retrieve images similar to query image. The performance of the proposed feature extraction technique is higher than the separate feature.

III.PROPOSED WORK

There are two modules employed in the proposed work. They are feature extraction and image clustering. Fig.1 shows the block diagram of proposed image retrieval system.

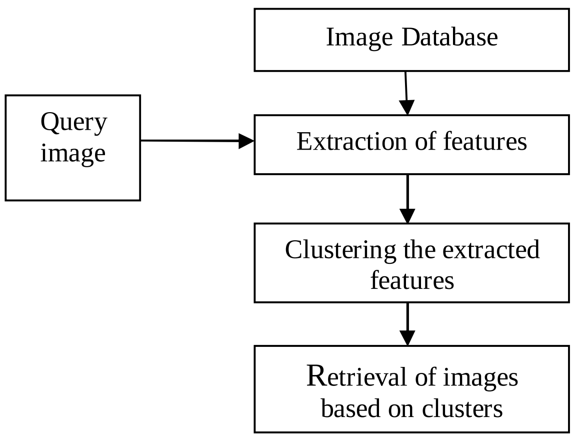

Fig.1 Block diagram of the proposed system

A. FEATURE EXTRACTION METHOD

Feature extraction is a process of reducing the amount of resources required to describe a large numbers of data. Analysis with a large set of variables generally requires a huge amount of memory and computation power. This is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient precision.

As mentioned in the related work (N.Nanthini, et al. (2017)), the proposed combination of SIFT and color histogram feature extraction method was employed here. In addition to that textures features are also combined to increase the efficiency. Color histogram, which represent the number of pixels of each color in the image. While sorting pixels, if a color space is huge, then it busted to intervals. SIFT (Scale-invariant feature transform) detects and uses a much larger number of features from the images, which reduces the contribution of errors caused by these local variations in the average error of all feature matching errors. It generates octaves and calculates difference of Gaussians and then it extracts the key points using Taylor expansion.

TEXTURE FEATURES

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 3, March 2017

Texture analysis aims in finding a unique way of representing the underlying characteristics of textures and represent them in some simpler but unique form, so that they can be used for robust, accurate classification and segmentation of objects. In this paper, Gray level co-occurrence matrix is formulated to obtain statistical texture features. Gray-level co-occurrence matrix gives the relative frequencies of occurrence of gray level combinations among pairs of image pixels. There are 14 kinds GLCM parameters. Here, five second order parameters namely contrast, correlation, energy, homogeneity and entropy are used. Let P(u,v) be the gray scale pixel which is used to calculate the GLCM parameters.

1. CONTRAST

$$I = \sum_u \sum_v (u - v)^2 P(u,v) \quad (1)$$

Moment of inertia will have a large value for images which have a large amount of local spatial variation in gray levels and a smaller value for images with spatially uniform gray level distributions.

2. ENERGY

$$E = \sum_u \sum_v [P(u,v)]^2 \quad (2)$$

Energy is the measure of gray distribution uniformity of image. The coarser the texture is, the more energy it contains.

3. CORRELATION

$$C = \frac{\sum_u \sum_v (u - \mu_1)(v - \mu_2) P(u,v)}{\sigma_u \sigma_v} \quad (3)$$

Where,

$$\mu_1 = \sum_u \sum_v u P(u,v)\ ,\ \mu_2 = \sum_u \sum_v v P(u,v) \quad (4)$$

$$\sigma_u^2 = \sum_u \sum_v (u-\mu_1^2) p(u,v),\ \ \sigma_v^2 = \sum_u \sum_v (u-\mu_1^2) p(u,v) \quad (5)$$

Correlation measures the linear dependency of grey levels of neighbouring pixels and also used to measure the degree of similarity of the elements in GLCM.

4. HOMOGENITY

$$H_\circ = \sum_u \sum_v \frac{P(u,v)}{1+|u-v|} \quad (6)$$

Homogeneity feature returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

5. ENTROPY

$$H = \sum_u \sum_v [P(u, v)] \log P(u, v) \quad (7)$$

Entropy is a measure of the amount of information of an image. Entropy relates to the texture information. If there is no texture information, the entropy is zero. After, above 5 GLCM parameters are computed. Then, the proposed feature extraction technique SIFT descriptor, color histogram and texture features are combined.

B. IMAGE CLUSTERING

The next module in the proposed work is image clustering. The clustering techniques are used to cluster individual pixels into groups that exhibit homogeneous properties, so that image within each cluster is similar in content. Clustering algorithms provide a useful tool to explore data structures.

In this work, three different clustering algorithms are used for image retrieval. To select the suitable clustering algorithm for image retrieval, spectral clustering, K-means and self-organizing map (SOM) are applied to cluster the extracted features.

Spectral clustering uses an affinity matrix to partition data into disjoint meaningful groups. Constructing such affinity graphs is a trivial task due to the ambiguity and uncertainty inherent in the raw data. Most existing spectral clustering methods typically adopt Gaussian kernel as the similarity measure and employ all available features to construct affinity matrices with the Euclidean distance, which is often not an accurate representation of the underlying data structures, especially when the number of features is large. [14]

1. K-MEANS CLUSTERING

K-means clustering is one of the clustering techniques. It partitions a collection of data into a K number group of data. It classifies a given set of data into K number of disjoint cluster. K-means algorithm consists of two separate

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

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Website: www.ijircce.com

Vol. 5, Issue 3, March 2017

phases. In the first phase it calculates the K centroid and in the second phase it takes each point to the cluster which has nearest centroid from the respective data point. K-means is an iterative algorithm in which it minimizes the sum of distances from each object to its cluster centroid, over all clusters.

Euclidean distance is the most used methods to define the distance of the nearest centroid. Once the clustering is done it recalculates the new centroid of each cluster and based on that centroid, a new Euclidean distance is calculated between each centre and data point. The centroid for each cluster is the point to which the sum of distances from all the objects in that cluster is minimized.

Let P(x, y) be an input pixels to cluster and c_k be the cluster centres. The algorithm for K-means clustering is following as;

Algorithm 1: Algorithm of clustering of images using proposed feature extraction and K-means algorithm

Step 1: Initialize number of cluster k and centre.

Step 2: For each extracted feature in the proposed combination method, calculate the Euclidean distance d, between the centre and each pixel of an image using the relation given below.

$$d = ||P(x, y) - c_k|| \quad (8)$$

Step 3: Assign all the key points to the nearest centre based on distance d.

Step 4: After all the proposed combined features have been assigned, recalculate new position of the centre using the relation given below.

$$c_k = \frac{1}{k}\sum_{y \epsilon c_k}\sum_{x \epsilon c_k} P(x, y) \quad (9)$$

Step 5: Repeat the process until it satisfies the tolerance or error value.

2. SELF-ORGANIZING MAP (SOM)

Self-organizing map is one of artificial neural network that is trained using unsupervised learning to produce a low-dimensional distinct representation of the input space of the training data, called map and is therefore a method to do dimensionality simplification. Self-organizing maps differ from other artificial neural networks as they apply competitive learning as against to error-correction learning and in the sense that they use a neighbourhood function to maintain the topological properties of the input space. SOM is based on competitive learning. Competitive learning is useful for clustering of input samples into a discrete set of output clusters. SOM is a technique which reduces the dimensions of data using Self-organizing neural networks.

SOM operates in two modules: i) Training builds the map using input. ii) Mapping automatically classifies a new input vector.

A self-organizing map consists of components called nodes. Grouped with each node's weight vector of the same dimension as the input data vectors, and a position in the map space. The usual arrangement of nodes is a 2D regular spacing in a rectangular grid. The self-organizing map describes a mapping from a higher-dimensional input space to a lower-dimensional map space. The procedure for placing a vector from data space onto the map is to find the node with the closest weight vector to the data space vector.

Initially the weights and learning rate are initialized. The input data to be clustered are presented to the network. Once the input vectors are given, based on the initial weights, the winning node called Best Matching Unit (BMU) is calculated either by Euclidean distance method or sum of products method. Based on the best matching unit selection, the weights are updated for that particular BMU using competitive learning rule. The SOM training process can be summarized in following steps:

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

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Vol. 5, Issue 3, March 2017

Algorithm 2: Algorithm of clustering of images using proposed feature extraction and SOM algorithm

Step 1: Initialize weight for each proposed combination of features (node).
Step 2: An input vector is chosen random from the set of training data.
Step 3: Every node is examined to calculate which one's weights are most likely to the input vector.
Step 4: The winning node is called Best Matching Unit (BMU). Then, the neighbourhood of BMU is calculated. The amount of neighbours decreases over time.

$$w(t+1) = w(t) + \Theta(v,t)\alpha(t)(D(t) - w(t)) \qquad (10)$$

where,

$w(t)$ = weight vector
$\alpha(t)$ = monotonically decreasing learning coefficient
$D(t)$ = the input vector
$\Theta(v, t)$ = neighborhood function

Step 5: The closer a node is to the BMU, the more its weights get altered and the farther away the neighbour is from the BMU, the less it learns.
Step 6: Repeat, step 2 for N iterations.

In this work, image features are extracted using histogram, texture and SIFT descriptors exclusively. As the combination of texture, histogram and SIFT features are needed to precisely define the image, so the fusion of histogram, texture and SIFT features are proposed in the work.

IV. RESULTS AND DISCUSSIONS

The proposed method is implemented in MATLAB. In this work, Corel-1k database is used. The database consists of 1000 images having 10 categories each of which has 100 images. Here, various feature extraction methods and clustering algorithms are implemented. In this work, experiments are conducted on the feature extraction of color histogram, texture feature and SIFT descriptors exclusively and proposed combination of them and three different clustering algorithms are used to cluster the similar extracted features of the images.

A. *PERFORMANCE MEASURES*

The efficiency of the image retrieval is based on the performance of the feature extraction and clustering algorithms. Here, Precision and Recall are the factors used for performance measurement.

1. *PRECISION*

The precision in image retrieval is the ratio of the retrieved relevant images to the query and total retrieved images.

$$Precision\ (P) = \frac{Number\ of\ Relevant\ image\ retrieved}{Total\ number\ of\ image\ retrieved}$$

2. *RECALL*

The recall in image retrieval is the ratio of the retrieved relevant images and total relevant images in the database.

$$Recall\ (R) = \frac{Number\ of\ Relevant\ image\ retrieved}{\begin{array}{c}Total\ number\ of\ relevant\ images\\ in\ the\ database\end{array}}$$

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Table 1.precision and recall values for each category using proposed feature extraction method with clustering algorithms

Categories	Spectral		K-means		SOM	
	Precision	Recall	Precision	Recall	Precision	Recall
Africans	0.867	0.764	0.718	0.633	0.770	0.679
Beaches	0.759	0.669	0.655	0.586	0.793	0.699
Buildings	0.925	0.816	0.827	0.705	0.933	0.832
Buses	0.805	0.710	0.716	0.631	0.925	0.816
Dinosaurs	0.917	0.809	0.867	0.764	0.965	0.851
Elephant	0.867	0.764	0.620	0.557	0.846	0.764
Roses	0.734	0.647	0.647	0.588	0.823	0.726
Horses	0.833	0.735	0.718	0.633	0.786	0.693
Foods	0.718	0.633	0.878	0.774	0.815	0.719
Mountains	0.827	0.705	0.608	0.564	0.965	0.851

To evaluate performance of the proposed system different categories of images are used. Table 1 shows that the precision and recall values for the proposed feature extraction method with all 3 clustering algorithms, it is found that self-organising map gives better performance than other spectral and K-means clustering algorithms.

Table 2. Average precision values for feature extraction methods

Clustering	Texture	Histogram	SIFT	Proposed method
Spectral	0.782	0.793	0.916	0.857
K-means	0.583	0.742	0.767	0.933
SOM	0.667	0.873	0.803	0.952

In Table 2 the average precision values for exclusive SIFT feature with SOM clustering is 0.803 and the proposed feature extraction method with SOM is 0.952.

Table 3. Average recall values for the feature extraction methods

Clustering	Texture	Histogram	SIFT	Proposed method
Spectral	0.670	0.679	0.845	0.734
K-means	0.518	0.684	0.708	0.861
SOM	0.592	0.805	0.741	0.878

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ISSN (Print): 2320-9798

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Vol. 5, Issue 3, March 2017

Similarly, in Table 3 the average recall values for exclusive SIFT with SOM is 0.741 and the proposed feature extraction method with SOM is 0.878. From the Table 2 & Table 3, it is inferred that the proposed combination of histogram, texture and SIFT feature extraction with SOM clustering gives better performance than exclusive of feature extraction methods.

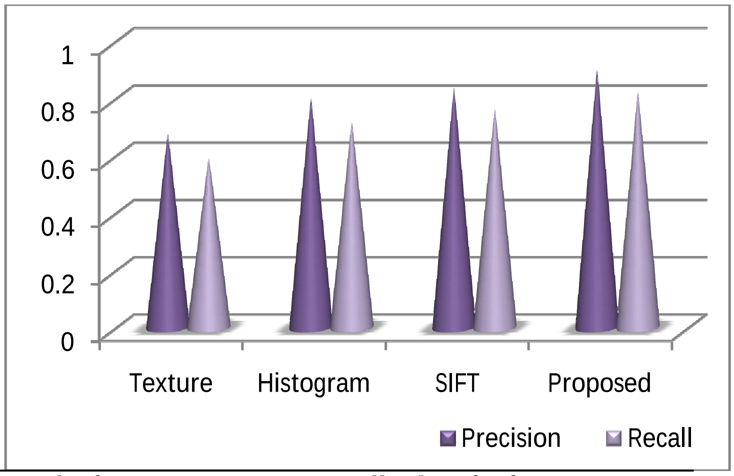

Fig.2 Graph of average precision & recall values for feature extraction methods

From Fig.2, it is observed that the average precision of the proposed feature extraction method of combination of histogram, texture and SIFT descriptors gives better results than exclusive Color histogram, texture features and SIFT descriptors separately. Fig.3 shows the GUI of the image retrieval system for the proposed methods.

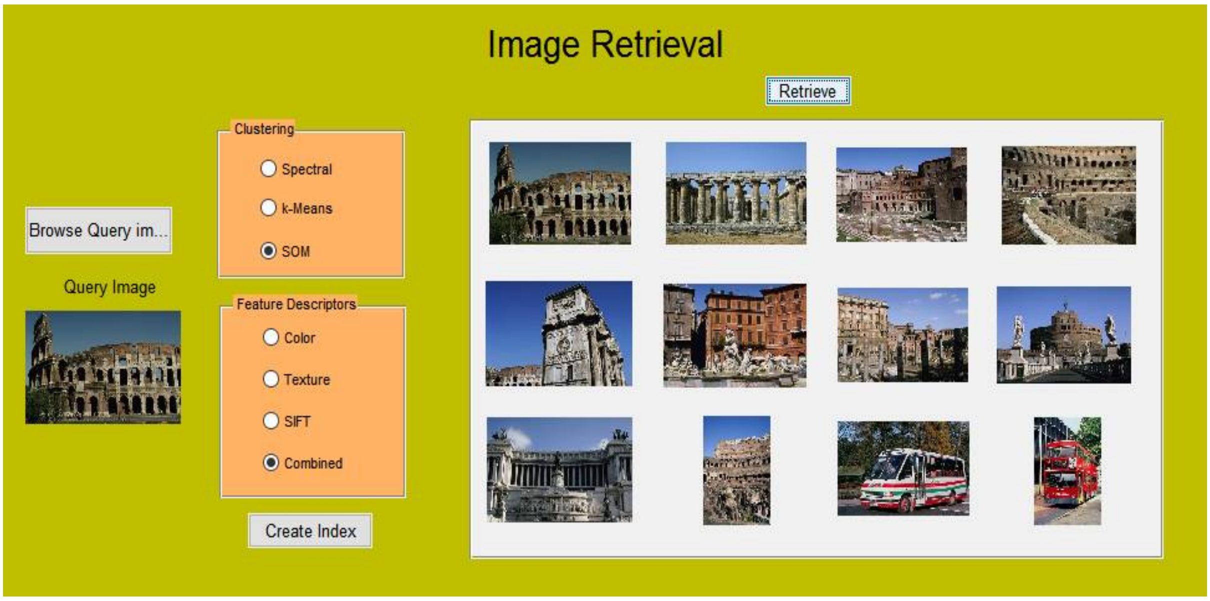

Fig.3 GUI of the image retrieval system

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ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 3, March 2017

V. CONCLUSION

In this work, proposed feature extraction method is implemented by using spectral, SOM and K-means clustering algorithms. All 4 feature extraction techniques are applied to 3 clustering algorithms, totally 12 combinations of image retrieval is done. The experiments results show that the precision values of the proposed combination of color histogram, texture and SIFT feature extraction is better than exclusive histogram, texture and SIFT features separately. Among the three clustering algorithms, it is observed that self-organising map gives high performance than spectral clustering and K-means clustering algorithms.

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