

Hadoop Based Image Retrieval Using CDLEP and Gabor Features

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Abstract— The Directional Extrema Patterns are used to encode the relationship between the centre pixel and its neighbors by computing the edge information in four directions. The proposed work focuses on developing a feature vector for CBIR system with the combination of color DLEP and Gabor features to make the final feature vector. Local Binary Pattern (LBP) operator has become very useful in image retrieval, where a centre pixel is compared with surrounding pixels to obtain a feature vector. However, the directions are not obtained in this method. In this paper, we propose a new method to improve the performance of the retrieval system with the help of Hadoop framework. The main objective is distribution of image data over a large number of nodes over Hadoop using Map Reduce Technique. Hadoop defines a framework which allows processing on distributed large sets across clusters of computer.

Key words: Color, Gabor Filters, LBP, DLEP, Image Retrieval, Hadoop, Mapreduce, Precision, Recall

I. INTRODUCTION

In recent times, due to the rapid growth in the Internet and allied areas huge number of images are created and stored across the globe in every second. Hence there is a need for a system which can search and index the images for various applications. The conventional text based annotation method becomes inefficient when the database size is large. Content based image retrieval (CBIR), has become an active area of research as an alternative to the existing methods in which, the visual contents such as color, texture, shape etc., are extracted to form a feature vector. The similarity between query image and the data base image is measured to retrieve more relevant images from the database. However, the efficiency of any CBIR system depends on the extraction of features such as color, texture, shape etc., to index and retrieve the images [1]-[3].

Among the features mentioned, texture provides more discriminating information. It is a visual feature that refers to the innate properties of the surface in an object and the relationship to the surrounding environment. Many techniques to classify and segment the texture can be found in the literature based on statistical analysis and structural methods. In [4], use of texture feature for classification of images was discussed. Arivazhagan et al [5] proposed texture classification using wavelet transform. In [6] texture classification and segmentation was proposed using wavelet packet frames and Gaussian mixture model. Gabor wavelets were used in texture classification for rotation invariant features [7].

Gabor filters have been used in the field of Image processing and texture analysis [10] for many years. It is a linear, band pass filter which is similar and close to human visual system. It gives the spatial frequency information.

A. Contribution

The existing directional local extrema pattern (DLEP) derives the directional edge information based on local extrema in 0°, 45°, 90°, and 135° directions of an image. In this paper, we propose combination of features such as color DLEP and Gabor to improve the performance of the existing Directional Local Extrema Pattern. The organization of this paper is as follows. The Section II reviews different types of local patterns. Section III explains Gabor feature. Section IV covers the proposed work for retrieval system. Section V contains the results. The conclusions are given in section VI.

In the proposed system we COMBINE CDLEP AND GABOR FEATURES for the efficient and effective retrieval of the image which incorporated with Map-Reduce framework such as Hadoop for fast calculation and return the result in shorter time. The Map-reduce framework works in parallel manner which processes on very large image collection of petabyte of storage.

B. Related work

A method based on Local Binary Pattern was introduced by Ojala et. al [8], the concept of LBP was extended to face recognition and other applications in [9]. However, LBP has the limitation of rotational invariance in classifying the texture present in an image. Local Derivative pattern by considering the n^{th} order Local Binary Pattern was proposed by Zhang et. al [11]. Subramanyam et al [12] proposed Directional Local Extrema Pattern as a feature vector for texture analysis of an image. An improvement to DLEP was proposed by Koteswararao et al [14],[15]. The DLEP is different from the existing Local patterns and other extensions in terms of directional information.

II. LOCAL PATTERNS AND VARIATIONS

A. Local Binary Pattern (LBP)

Local binary pattern was introduced by T Ojala [8]. In this, the value of the centre pixel is considered as threshold and the difference between centre pixel and its surrounding neighbors is taken into consideration to assign a binary 0 or 1. The method is repeated till all the pixels surrounding the centre pixel are covered in the process.

$$LBP_{P,R} = \sum_{p=0}^{p-1} k(g_p - g_c)2^p, k(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

where g_c represents the gray value of center pixel and g_p represents the gray value of P equally spaced pixels on circumference of the circle with radius R.

B. Local Directional Pattern (LDP)

Local Directional Pattern [14] is based on LBP which uses the edge response of neighborhood pixels in order to encode the texture in an image. It assigns an eight bit binary code to each pixel of an input image.

A binary value of 1 or 0 is assigned based on the presence of an edge.

$$LDP_n = \sum_{i=1}^8 f_i(m_i - m_k) * 2^i, f_i(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}$$

C. Directional Local Extrema patterns (DLEP)

DLEP was introduced by Subrahmanyam et al [12].It describes the spatial structure of the local texture using the local extrema of center gray pixel g_c . The local extrema values in four directions are obtained by taking the difference between the centre pixel and all its neighbors.

The calculation is as shown below.

$$I'(g_i) = I(g_c) - I(g_i); i = 1, 2, \dots, 8$$

The local extremas are based on the equations given below.

$$I_\alpha(g_c) = S_3(I'(g_i) * I'(g_{j+4})); j = (1 + \alpha / 45)$$

$$\forall \alpha = 0^0, 45^0, 90^0, 135^0$$

$$S_3(I'(g_j), I'(g_{j+4})) = \begin{cases} 1 & I'(g_j) * I'(g_{j+4}) \geq 0 \\ 0 & \text{else} \end{cases}$$

The DLEP is computed as $(\alpha=0^0, 45^0, 90^0 \text{ and } 135^0)$ as follows:

$$DLEP(I(g_c))|_\alpha = \{I_\alpha(g_c); I_\alpha(g_1); I_\alpha(g_2); \dots; I_\alpha(g_8)\}$$

The details of DLEP can be found in figure1. In the next step, the given image is converted into DLEP images with values ranging from 0 to 511.

After calculation of DLEP, the whole image is represented by building a histogram based on the equation mentioned below.

$$H_{DLEP} |_\alpha(i) = \sum_{j=1}^{X_1} \sum_{k=1}^{X_2} f_2(DLEP(j, k)|_\alpha, \ell);$$

$$\ell \in [0, 511]$$

where the size of input image is $X_1 \cdot X_2$. The procedure for calculation of DLEP for center pixel marked in green color is presented in fig.1. The directions are evaluated using the local difference between the center pixel and its neighbors.

As an example, the DLEP in 90^0 direction for a center pixel marked in green color is shown in the figure2. For the center pixel value 27, it can be observed that two neighboring pixels are leaving. Therefore, this pattern is represented as 1. In the same way the rest of the bits of DLEP pattern are calculated and the result is 110011110. Similarly, the DLEP's are computed for $0^0, 45^0$ and 135^0 directions. The improved DLEP is given in [13].

III. GABOR FEATURE

The Gabor filter is found to be efficient for text representation and discrimination. The representation of 2-D Gabor filter is as specified below.

$$\Psi_{f,\theta}(x, y) = \exp\left[-\frac{1}{2}\left\{\frac{x^2\theta_n}{\sigma^2x} + \frac{y^2\theta_n}{\sigma^2y}\right\}\right] \exp(2\pi fx\theta_n)$$

Here S is the central frequency of sinusoidal plane and θ is the orientation of x y plane.

$$\begin{bmatrix} x\theta_n \\ y\theta_n \end{bmatrix} = \begin{bmatrix} \sin \theta_n & \cos \theta_n \\ -\cos \theta_n & \sin \theta_n \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} (n-1)$$

θ_n is the rotation of xy plane by θ_n angle results gabor filter at the orientation θ_n .

$$\text{angle } \theta_n = \frac{\pi}{p}$$

where $n=1, 2, \dots, p, p \in \mathbb{N}$ and p is the orientation.

51	33	69	75	57
19	78	85	63	12
36	13	27	29	42
48	88	87	80	65
11	53	95	91	84

Fig. 1: Illustration of DLEP for 3 x 3 pattern

	0 ₍₂₇₎	1 ₍₂₉₎	2 ₍₈₀₎	3 ₍₈₇₎	4 ₍₈₈₎	5 ₍₁₃₎	6 ₍₇₈₎	7 ₍₈₅₎	8 ₍₆₃₎	DL EP
P (0 ⁰)	0	0	0	0	1	1	0	1	0	26
Q(45 ⁰)	1	0	0	1	1	1	1	0	1	317
R(90 ⁰)	1	1	0	0	1	1	1	1	0	415
S(135 ⁰)	1	1	0	0	0	1	1	1	0	398

Table 1:

Fig. 2: Example to compute DLEP in 900 direction (110011110)

IV. HADOOP FRAMEWORK

Hadoop provides open source software framework which is used for storage and large scale processing of datasets on clusters. It has two subparts, Map-reduce and HDFS, Mapreduce for computational capabilities and HDFS for storage. Map-reduce is distributed framework for data processing, especially big data. The Map-reduce process of hadoop complete with two phases Map and Reduce. In Map phase stored split data inputted to map function which will generate intermediate key pair.

Wherever reduce phase accept these key value pair as its inputs which will merge all intermediate values associated with same intermediate key. Fig 3 below shows architecture of HDFS.

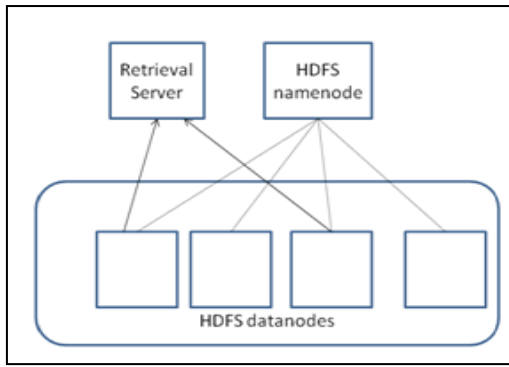


Fig. 3: architecture of HDFS

Hadoop is a framework that allows for the distributed processing of large datasets, it is also capable of to process small datasets. However it also works on terabyte of data where RDBMS takes hours and fails whereas Hadoop does the same in couple of minutes. The Apache Hadoop is an open-source software project for scalable, reliable, flexible, distributed computing, failure handling.

HDFS - In HDFS Data is divided into chunks. Namenode is the Master of the File System and Datanode is the slave Component of the file system, only one Namenode and multiple Namenode are running on the Hadoop cluster. Data to be stored on node that is Datanode. Datanode should be replicated one each Datanode, if one data node goes down then the data is present on another Datanode also the Name node knows where the data is to be stored in which rack. Namenode contain all the data storage information which is stored in Datanode. There is another Namenode that also contain all the information like Namenode called secondary Namenode. If Namenode fails then it will recover the information from secondary Namenode.

Map Reduce - The parallel framework offered by Map- reduce is highly suitable for proposed CBIR structure with large amount of data. Figure 4 shows the Map reduce technique. We use the open source distributed cloud computing framework hadoop and their implementation of Map-reduce module. Map-Reduce decomposes work submitted by a client into a small parallelized map and reduce jobs, as shown in figure 3. Fig 4. shows a multi-node Hadoop cluster. Hadoop provides location awareness compatible file system. In HDFS Data is divided into chunks. Namenode is the Master of the File System and Datanode is the slave Component of the file system, only one Namenode and multiple Namenode are running on the Hadoop cluster. Data to be stored on node that is Datanode [16]-[18].

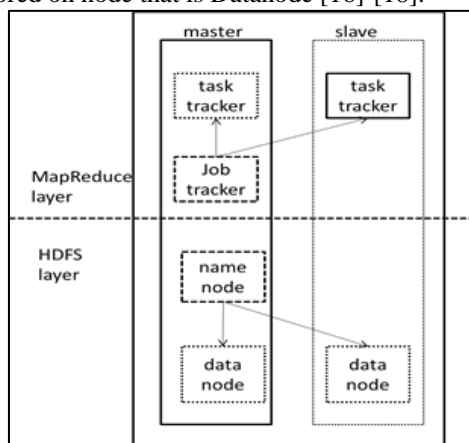


Fig. 5: shows working principle of hadoop map-reduce.

Datanode should be replicated one each Datanode, if one data node goes down then the data is present on another Datanode also the Name node knows where the data is to be stored in which rack. Namenode contain all the data storage information which is stored in Datanode. There is another Namenode that also contain all the information like Namenode called secondary Namenode. If Namenode fails then it will recover the information from secondary Namenode [12].

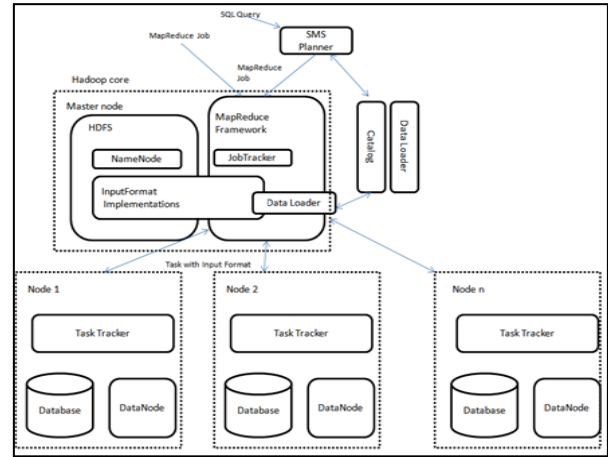


Fig. 5: Working principle of Map reduce

A. Proposed System

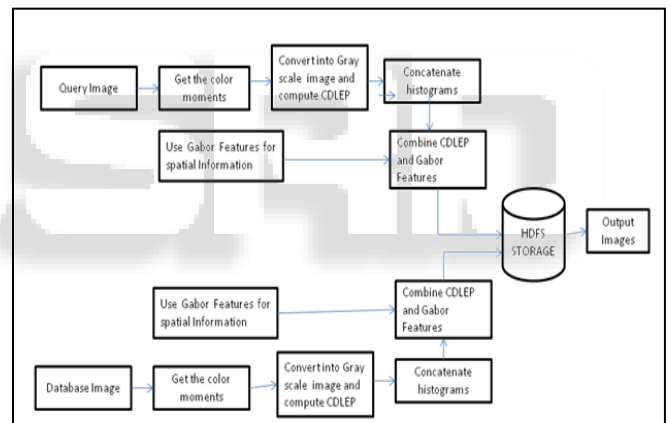


Fig. 6: Framework of the proposed method

B. Proposed Algorithm

- 1) Compute the color moments for the given image and then convert RGB image into gray scale image.
- 2) Use Gabor filter to get the spatial information.
- 3) Compute the local extrema in $0^0, 45^0, 90^0$ and 135^0 directions.
- 4) Compute the CDLEP patterns in four directions mentioned in step 2.
- 5) Get a histogram for the DLEP patterns obtained in step 3 and concatenate to get the texture feature vector.
- 6) Combine these two features to get a feature vector that can be used in image retrieval

C. Query Matching

Once the features are extracted, the feature vector for query image is obtained. In the same manner, feature vectors for all images in the database are also calculated. To select the more relevant image to the query image, the distance between query image and database images is calculated.

V. EXPERIMENTAL RESULTS

Performance of the CDLEP is evaluated on standard corel-1k database. The precision(P) and recall (R) values are computed as per the relationship mentioned here under.

$$P = \frac{\text{No. of relevant images retrieved}}{\text{No. of images retrieved}}$$

$$R = \frac{\text{No. of relevant images retrieved}}{\text{No. of relevant images in the database}}$$

The top ten results for different categories of the data base are shown in the table 1.

Category	Existing DLEP	PM
Africans	69.3	82
Beach	60.5	84
Building	72.0	100
Buses	97.9	98
Dinosaur	98.5	100
Elephant	55.9	84
Flower	91.9	100
Horse	76.9	100
Mountain	42.7	65
Food	82.0	94
Average Precision (%)	74.8	90.7

Table 1: Comparison of precision values for DLEP and Proposed method

Category	DLEP	PM
Africans	39.7	42
Beach	37.3	41
Building	34.9	44
Buses	74.1	78
Dinosaur	88.0	89
Elephant	29.0	35
Flower	70.8	84
Horse	41.7	43
Mountain	29.0	32
Food	47.0	49
Average Recall (%)	49.16	53.7

Table 2: Comparison of recall values for DLEP and Proposed method

The comparisons in terms of average precision and recall are given in the graph given below.

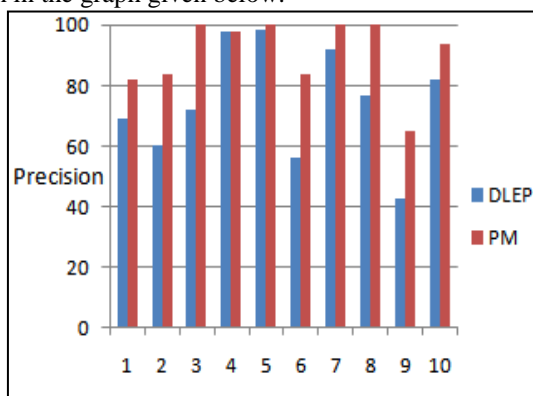


Fig. 7: category- wise performance in terms of precision

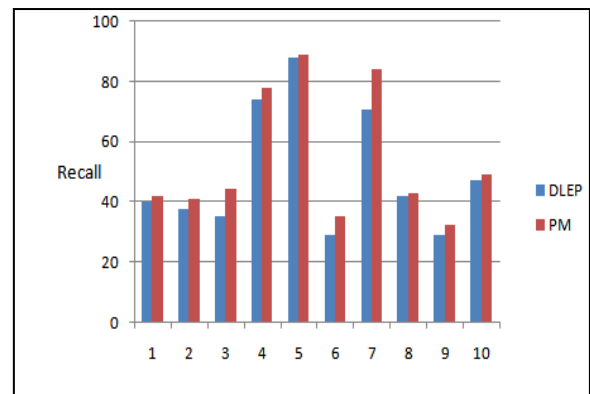


Fig. 8: category- wise performance in terms of recall

VI. CONCLUSIONS

In this system the image stored on the HDFS database of Hadoop is in the text format which will not give any information the about the images on database even to the database admin. Thousands of images are growing through the various digital devices and these images are added to the image databases and internet for various applications which needs to store and retrieve the images in effective and efficient manner. Hadoop distributed File system (HDFS) is used to store and retrieve images. Application developed using the proposed approach is fast and efficient in retrieving images. The content based image retrieval algorithm used in the developed application produces accurate results within short span of time and is very reliable. The Hadoop-CBIR developed has immense potential to be used in various fields. This paper presents a content based image retrieval system in Hadoop framework Hadoop has been used in this work to set up a grid in a large scale environment which supports large amount of data processing. It also facilitates accurate retrieval of images matching the queried image. As the proposed image retrieval system is implemented in Hadoop, it is very easy to adapt in cloud environment with minimal overhead.

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