Enhancing the CBIR Technique for Image Analysis through Machine Learning Algorithm

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Abstract: *- This paper introduces a content Based Image Retrieval (CBIR) based on evolutionary algorithm. Initially, the shape, color and texture feature is extracted for the given query image and also of the database images in a similar manner. Subsequently, similar images are retrieved utilizing an evolutionary algorithm based similarity. Thus, by means of the evolutionary algorithm, the required relevant images are retrieved from a large database based on the given query. The CBIR system is evaluated by querying different images and the efficiency of the system is evaluated by means of the precision-recall value of the retrieved results.*

Keywords- Feature extraction, shape, color histogram, texture, query, Evolutionary Algorithm (EA)

I. Introduction: Images are widely used nowadays. It has the advantage of visual representation and it is usually adopted to express other mediums. With the rapid development of computers and networks, the storage and transmission of a large number of images become possible. Instead of text retrieval, image retrieval is wildly required in recent decades. Content-based image retrieval (CBIR) is regarded as one of the most effective ways of accessing visual data. It deals with the image content itself such as color, shape and image structure instead of annotated text. Huge amounts of data retrieval challenge the traditional database technology, but the traditional text-object database cannot satisfy the requirements of an image database. The traditional way of an annotated image using text, lacks the automatic and effective description of the image. In order to implement CBIR, the system need to understand and interpret the content of managed images. The retrieval index should be produced automatically, which provides more a visual retrieval interface to users. [1]

CBIR refers to image content that is retrieved directly, by which the images with certain features or containing certain content will be searched in an image database. The main idea of CBIR is to analyze image information by low level features of an image which include color, texture, shape and space relationship of objects etc., and to set up feature vectors of an image as its index. Retrieval methods focus on similar retrieval and are mainly carried out according to the multidimensional features of an image. As images are rich in content and without language restrictions to facilitate international exchanges, etc., CBIR has very broad and important applications in many areas including military affairs, medical science, education, architectural design, the justice department and agriculture, etc. Many CBIR systems have been developed gradually. Typical examples of the CBIR retrieval systems include QBIC, Virage, Photo-book, Visual Seek, Netra and Simplicity etc. The progress of CBIR research was lucidly summarized at a high level in [2, 9]. Features are the basis for CBIR, which are certain visual properties of an image. The features are either global for the entire image or local for a small group of pixels. According to the methods used for CBIR, features can be classified into low-level features and high-level features.

II. Related Work

Pugalendhi, Ganesh Kumar. (2018) [1] shows that the Content-based image retrieval (CBIR) uses image content features to search and retrieve digital images from a large database. A variety of visual feature extraction techniques have been employed to implement the searching purpose. Due to the computation time requirement, some good algorithms are not been used. The retrieval performance of a content-based image retrieval system crucially depends on the feature representation and similarity measurements. The ultimate aim of the proposed method is to provide an efficient algorithm to deal with the above mentioned problem definition. Here the deep belief network (DBN) method of deep learning is used to extract the features and classification and is an emerging research area, because of the generation of large volume of data. The proposed method is tested through simulation in comparison and the results show a huge positive deviation towards its performance.

Ouhda, Mohamed et al. (2018) [2] Present the study on today's world is digital with the appearance of many devices that are used in image acquisition. Nowadays, it becomes easy to store huge amount of images by using image processing techniques. The rapid access to these masses collections of images and retrieve similar images of a given image (Query) from this huge collection of images presents major challenges and requires efficient algorithms. The main goal of the proposed system is to provide an accurate result with lower computational time. For our purpose, we introduce in the content based image retrieval (CBIR) system the classification step, and we apply k-means clustering technique to match image's descriptors. This work provides a detailed view of the solution we have adopted, and that perfectly meets our needs. For validation, we apply all of these techniques on two image databases in order to evaluate the performance of our system.[l]

Jindal, Sonika & Seth, Nitika (2017) [3] write an article on Image retrieval that means to recover the original image from the reconstructed image, here in this paper we have discussed latest techniques in the field of image retrieval for image processing. Content Based Image Retrieval (CBIR) is one of the most exciting and fastest growing research areas in the field of Image Processing. The techniques presented are Boosting image retrieval, soft query in image retrieval system, content based image retrieval by integration of metadata encoded multimedia features, and object based image retrieval and Bayesian image retrieval system. Some probable future research directions are also presented here to explore research area in the field of image retrieval.

Gordo et al. (2016) [4] propose a novel approach for instance-level image retrieval. It produces a global and compact fixed-length representation for each image by aggregating many region-wise descriptors. In contrast to previous works employing pre-trained deep networks as a black box to produce features, our method leverages a deep architecture trained for the specific task of image retrieval. Our contribution is twofold:

(i) They leverage a ranking framework to learn convolution and projection weights that are used to build the region features; and

(ii) They employ a region proposal network to learn which regions should be pooled to form the final global descriptor.

They show that using clean training data is key to the success of our approach. To that aim, they use a large scale but noisy landmark dataset and develop an automatic cleaning approach. The proposed architecture produces a global image representation in a single forward pass. Our approach significantly outperforms previous approaches based on global descriptors on standard datasets. It even surpasses most prior works based on costly local descriptor indexing and spatial verification.

Liu et al. (2016) [5] present a new hashing method to learn compact binary codes for highly efficient image retrieval on large-scale datasets. While the complex image appearance variations still pose a great challenge to reliable retrieval, in light of the recent progress of Convolutional Neural Networks (CNNs) in learning robust image representation on various vision tasks, this paper proposes a novel Deep Supervised Hashing (DSH) method to learn compact similarity-preserving binary code for the huge body of image data. Specifically, they devise a CNN architecture that takes pairs of images (similar/dissimilar) as training inputs and encourages the output of each image to approximate discrete values (e.g. +1/-1). To this end, a loss function is elaborately designed to maximize the discriminability of the output space by encoding the supervised information from the input image pairs, and simultaneously imposing regularization on the real-valued outputs to approximate the desired discrete values. For image retrieval, new-coming query images can be easily encoded by propagating through the network and then quantizing the network outputs to bi- nary codes representation. Extensive experiments on two large scale datasets CIFAR-10 and NUS-WIDE show the promising performance of our method compared with the state-of-the-arts.

Babenko & Lempitsky (2015) [6] introduced several recent works have shown that image descriptors produced by deep convolutional neural networks provide state-of-the-art performance for image classification and retrieval problems. It has also been shown that the activations from the convolutional layers can be interpreted as local features describing particular image regions. These local features can be aggregated using aggregation approaches developed for local features (e.g. Fisher vectors), thus providing new powerful global descriptors. In this paper they investigate possible ways to aggregate local deep features to produce compact global descriptors for image retrieval. First, they show that deep features and traditional hand-engineered features have quite different distributions of pairwise similarities, hence existing aggregation methods have to be carefully re-evaluated. Such re-evaluation reveals that in contrast to shallow features, the simple aggregation method based on sum pooling provides arguably the best performance for deep convolutional features. This method is efficient, has few parameters, and bears little risk of over fitting when e.g. learning the PCA matrix. Overall, the new compact global descriptor improves the state-of-the-art on four common benchmarks considerably.

Liang, R. *et al.* (2016) [7] in this paper they study the problem of content-based image retrieval. In this problem, the most popular performance measure is the top precision measure, and the most important component of a retrieval system is the similarity function used to compare a query image against a database image. However, up to now, there is no existing similarity learning method proposed to optimize the top precision measure. To fill this gap, in this paper, they propose a novel similarity learning method to maximize the top precision measure. They model this problem as a minimization problem with an objective function as the combination of the losses of the relevant images ranked behind the top-ranked irrelevant image, and the squared frobenius norm of the similarity function parameter. This minimization problem is solved as a quadratic programming problem. The experiments over two benchmark data sets show the advantages of the proposed method over other similarity learning methods when the top precision is used as the performance measure.

Zhang, R (2015) [8] Extracting informative image features and learning effective approximate hashing functions are two crucial steps in image retrieval. Conventional methods often study these two steps separately, *e.g.*, learning hash functions from a predefined hand-crafted feature space. Meanwhile, the bit lengths of output hashing codes are preset in most previous methods, neglecting the significance level of different bits and restricting their practical flexibility. To address these issues, they propose a supervised learning framework to generate compact and bit-scalable hashing codes directly from raw images. They pose hashing learning as a problem of regularized similarity learning. Specifically, they organize the training images into a batch of triplet samples, each sample containing two images with the same label and one with a different label. With these triplet samples, they maximize the margin between matched pairs and mismatched pairs in the Hamming space. In addition, a regularization term is introduced to enforce the adjacency consistency, *i.e.*, images of similar appearances should have similar codes. The deep convolutional neural network is utilized to train the model in an end-to-end fashion, where discriminative image features and hash functions are simultaneously optimized. Furthermore, each bit of our hashing codes is unequally weighted so that they can manipulate the code lengths by truncating the insignificant bits. Our framework outperforms state-of-the-arts on public benchmarks of similar image search and also achieves promising results in the application of person re-identification in surveillance. It is also shown that the generated bit-scalable hashing codes well preserve the discriminative powers with shorter code lengths.

Guo & Prasetyo (2015) [9] this paper presents a technique for Content-Based Image Retrieval (CBIR) by exploiting the advantage of low complexity Ordered-Dither Block Truncation Coding (ODBTC) for the generation of image content descriptor. In encoding step, ODBTC compresses an image block into corresponding quantizes and bitmap image. Two image features are proposed to index an image, namely Color Co-occurrence Feature (CCF) and Bit Pattern Features (BPF), which are generated directly from ODBTC encoded data streams without performing the decoding process. The CCF and BPF of an image are simply derived from the two ODBTC quantizes and bitmap, respectively, by involving the visual codebook. Experimental results show that the proposed method is superior to the Block Truncation Coding (BTC) image retrieval systems and the other former methods, and thus prove that the ODBTC scheme is not only suited for image compression since of its simplicity, but also offers a simple and effective descriptor to index images in CBIR system.

Dureja, A., & Pahwa, P. (2017) [10] introduce of different techniques from the use of visual features for shooting, as well as the latest technology to study deep CNNs by number of layers, is now the best method to capture images from large databases. In the end, analyzes of various development techniques and show the pros and cons of technology.

III. Methodology Used for CBIR

1) Color Histogram Feature Extraction: In this feature extraction phase, the features of the images are extracted. Initially, the color histogram of the image is to be extracted. For extracting the color histogram feature, initially the image 1 must be first re-sampled and then subjected to the segmentation process. The anisotropic diffusion segmentation is applied on the re-sampled image "I" and it discretizes the family of continuous partial differential equations, which incorporates both the physical processes of diffusion and the Laplacian. The image segmentation process can be represented using the following equation,

oj =div(c(m,n,t)'VJ)='Vc.'VJ +c(m,n,t)M …..**(1)**

Where II denotes the Laplacian, 'V denotes the gradient, divis the divergence operator and c (m,n,t) is the diffusion coefficient. C (m, n, t) controls the rate of diffusion and is usually chosen as a function of the image gradient so as to preserve edges in the image. After the segmentation process, the color histogram C of the image j is computed. Then for all the database images the color histogram feature is extracted in a similar manner.

2) Shape Feature Extraction: In order to extract the shape feature, the image 1 is first transformed into a grayscale image 1 gr using the Craig's formula for converting an RGB color space image into a grayscale image as shown in eqn (2).

$I\ gr = 0.2989 * r + 0.5870 * g + 0.1140 * b$ …. **(2)**

Here r, g, bare the R, G, B values of the image. Then the obtained grayscale image I gr is denoised using filters. Then the noise-free grayscale image is subjected to the clustering process. Our work utilizes the k-means clustering algorithm to identify the various regions of the denoised image 1 gr and the following algorithm details the process Input: Image 1 gr with m x n pixels K -number of clusters Output: set of K-clusters

Step 1: Arbitrarily select K data items from the input as initial centroids.

Step 2: Assign the remaining data items apart from the selected initial centroids to the cluster K that has the closest centroid

Step 3: clustering for the data sets.

Step 4: Calculate the new centroid for each Repeat steps 2 and 3 until convergence occurs. Thus, the clustered regions are identified by means of the k-means clustering algorithm and then the edges are detected using a canny edge detection technique. The following are the steps involved in the canny edge detection technique.

Machine learning is the combinational effort of the detection of image as well as the image analysis with help of specific algorithms that is needed to perform the complete analysis.

IV. Algorithm for CBIR using Machine Learning

1. established the parameters pop_ size, pc, pm, WL-initial and WL-final.

2. Produce the initial population.

3. Investigate the fitness based on similarity difference.

4. Put on crossover according to Pc parameter.

5. Put on Mutation.

6. Put on great deluge algorithm native search.

7. Estimate the fitness based on likeness variance.

V. Conclusion

In this paper, we investigate various efficient CBIR system which retrieves the relevant images from a large database for a given query image using color, histogram shape and with the current technology Machine Learning. Initially, the CBIR system extracts the color, shape and texture features from the query image as well as from the database images. After that process, the enhancing the present algorithm (Machine Learning) which applied to obtain the relevant images for the given query image. The CBIR system was evaluated using different query images. The implementation results show that the investigation of CBIR system retrieves relevant images from the database in an effective manner. The precision-recall computed from the retrieval results demonstrated the efficiency of the CBIR system.

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