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Towards a Content Based Image Retrieval Approach

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Abstract:
Nowadays Content Based Image Retrieval is getting more and more attention from organizations, governments and researchers because of the large number of images available in databases across the world. There is a growing interest to search for images in Multimedia databases since they carry most of the intended messages and are very expressive. However, it is not only difficult but time-consuming task to perform. Because of large collection of images to search from. This paper reviews current trends in the area of area of Content Based Image Retrieval and highlights areas which need improvement.

Keywords*: Image retrieval, text-based image retrieval, content-based image retrieval, distance measures, texture, shape, performance evaluation, precision, recall*

1. Introduction

Content based Image Retrieval is generally called as Query by Image Content (Cui, Lin, Nie, Yin, & Zhu, 2017a). The term 'content based' refers to the analysis of the image given as query (Guissous & Gouet-Brunet, 2017). The term content may refer to the texture, color, shape or some other element that can be referred from the image itself (Cui et al., 2017a). The digital photography had made many advances which helped in storing the large amounts of high quality images and also helped in increasing the networks speed (Lonarkar & Rao, 2017). An image retrieval system refers to a PC framework that helps in searching and recovering images from a huge database of images. Retrieval of images is separated into two sorts of retrieval systems that is Text based Image Retrieval and Content based Image Retrieval (Babu, Vanitha, & Anish, 2016). Retrieval of images is separated into two sorts of retrieval systems that is Text based Image Retrieval and Content based Image Retrieval(Babu et al., 2016). Most of the engines present depends on text based image retrieval where image retrieving is based on the keywords displayed along with image(Babu et al., 2016) .

2. Image Retrieval

Early work on image retrieval can be traced back to the late 1970s. In 1979, a conference on Database Techniques for Pictorial Applications was held in Florence (Tyagi, 2018). Since then, the research in the area of image database management techniques has attracted the attention of many researchers (Tyagi, 2018). In (Lonarkar & Rao, 2017) a comprehensive survey highlighting progress in image retrieval research, emerging directions, and other relevant topics related to CBIR has been provided. The most common image retrieval systems are text-based image retrieval (TBIR) systems, where the search is based on automatic or manual annotation of images (Tyagi, 2018).

Early image search techniques were generally based on the textual annotation of images(Tyagi, 2018). In other words, images were first annotated with text and then searched using a text-based approach from traditional database management systems.

2.1. Text Based

Text-based image retrieval uses traditional database techniques to manage images (Tyagi, 2018). Through text descriptions, images can are organized by topical or semantic hierarchies to facilitate easy navigation and browsing based on standard Boolean queries (Tyagi, 2018).Since it is not feasible to automatically generate descriptive texts for a wide spectrum of images, most text-based image retrieval systems require Manual Annotations (Cai, Gao, Yu, Huang, & Cai, 2017).It is currently the most common means of image retrieval (Tyagi, 2018). In this approach, images are first annotated with text and then searched using a text-based approach from traditional database management systems (Tyagi, 2018). Annotating images manually is a cumbersome and expensive task for large image databases, and is often subjective, context-sensitive and incomplete. As a result, it is difficult for the traditional text-based methods to support a variety of task-dependent queries.

2.2. Content Based

In (Celik & Bilge, 2017), a content based image retrieval approach based on color and texture features is introduced(Celik & Bilge, 2017).The model is implemented in two steps where in the first step, HSV Color space is quantified rationally and color histogram and texture features are extracted to form feature vectors (Celik & Bilge, 2017).In the second step the characteristics of the global color histogram, local color histogram and texture features are compared and analyzed for CBIR (Celik & Bilge, 2017). Wang and coli20 datasets were used in the paper and the model implemented using Java under the Eclipse development environment. SQL server 2005 served as the system database (Celik & Bilge, 2017). The paper obtained a Mean Average Precision of 58% for Wang dataset and 89% for coli20 dataset (Celik & Bilge, 2017). It can be appreciated that the model fused both color and texture features which is a step forward in CBIR research. However, an average precision of 58% is low and implies that the model is almost wrong half the iterations.

In (Alsmadi, 2017) a content based image retrieval using memetic algorithm is introduced (Alsmadi, 2017). In the work, features were extracted from the images database and then stored in the feature repository(Alsmadi, 2017). The feature set was color signature with the shape and color texture features (Alsmadi, 2017).Similarity evaluation was done using a meta-heuristic algorithm called a memetic algorithm (Alsmadi, 2017) . The Research assessed the developed model's efficiency in terms of precision and recall. The dataset used was Wang 1000 Images(Alsmadi, 2017). The experimental results of the model were encouraging since it had an average precision of 0.8 which is an advanced move towards accuracy. However, the model has an average precision of 0.7 in Class Building which means the model perform so poorly in that class thus it cannot be applied on it. It can also be observed average precision obtained in this research can still be improved.

In (Mistry, Ingole, & Ingole, 2017a) a Content based image retrieval using color and texture features is proposed (Mistry, Ingole, & Ingole, 2017b). The following distance metrics: Euclidian, City Block, Minkowski and Mahalanob were applied(Mistry et al., 2017b) Features are extracted using HSV histogram, Binarized Statistical Image Features (BSIF), Color and Edge Directivity Descriptors (CEDD) and Color moments (Mistry et al., 2017b). Feature extraction using HSV histogram includes color space conversion, color quantization and histogram computation (Mistry et al., 2017a). Binarized statistical image features, color and edge directivity descriptor features were employed to aid precision Mistry et al., 2017a). The experiments were performed using WANG database which consists of 1000 images from 10 different classes(Mistry et al., 2017b). The precision of the developed model was 0.75(Mistry et al., 2017a) which is higher than 0.703 which was the precision in (Youssef, Mesbah, & Mahmoud, 2012).It can be noted that the research is a remarkable improvement in terms of precision. However better precision levels has been achieved by other authors including (Alsmadi, 2017) and (Celik & Bilge, 2017)

In (Karamti, Tmar, & Gargouri, 2014) a Content-based image retrieval model using neural network is proposed. It allowed to integrate theories of neural network on a vector space model, where each low level query could be transformed into a score vector (Karamti et al., 2014).In the research, an image retrieval model has been implemented with a general image database (Karamti et al., 2014). The images are stored in JPEG format with size 384 × 256 or 256 × 384 (Karamti et al., 2014). For the evaluation of the model, two different image databases were used : Corel[1] and Caltech-UCSD[2] (Karamti et al., 2014).The Corel database in formed by 68040 images from various categories (African people and villages, beach, buildings, buses, dinosaurs, elephants, flowers, horses, mountains and glaciers, food, etc.) (Karamti et al., 2014). The Caltech – UCSD is an image dataset with photos bird species formed with 6033 images from 200 categories(Karamti et al., 2014).The research produces its best precision at 75% after several iteration. This is a significant improvement in the field but we do recognize that better levels of accuracy has been achieved in other studies including (Alsmadi, 2017) and (Celik & Bilge, 2017)

In (Bai, Huang, Pan, Zheng, & Chen, 2018),a Content Based Image Retrieval using Neural has been proposed with Network Distance metric Learning and Artificial Neural Network used to measure the similarity between images (Bai et al., 2018). The research uses WANG Database of 90 images (Bai et al., 2018).The first step is where query image is given, then low level features like color, texture and shape are extracted from the query image (Bai et al., 2018). For color feature extraction three color moments are used in three color channels (HSV), So there are 9 color features (Bai et al., 2018). Total 36 features of Query image are extracted and a feature vector is then calculated (Bai et al., 2018). After Feature extraction next step is similarity measurement (Bai et al., 2018) where Distance Metric Learning (DML) and Artificial Neural Networks are used(ANN) (Bai et al., 2018). The top closest images to the query image are retrieved (Bai et al., 2018) and the search is usually based on similarity rather than exact match (Bai et al., 2018).The results of the research showed that ANN produced more accurate results than DML algorithm(Bai et al., 2018). Relevance feedback mechanism is also used in the project which improves the retrieval accuracy(Bai et al., 2018).The best precision level is 69% which is a bit lower than other reviewed studies. It can also be noted that 90 images used in the study is less and thus prone to biasness.

In (Aboulmagd, El-Gayar, & Onsi, 2013), a new approach in content-based image retrieval using fuzzy is provided. In this study a fuzzy logic is used to improve CBIR by allowing users to express their requirements in words, the natural way of human communication(Aboulmagd et al., 2013).The data used in the research is Microsoft dataset[3] consisting originally of 591

[1] https://archive.ics.uci.edu/ml/datasets/Corel+Image+Features
[2] http://vision.caltech.edu/visipedia/CUB-200.html
[3] http://research.microsoft.com/vision/cambridge/recognition/

images containing 23 different object classes(Aboulmagd et al., 2013). In the proposed model, the image is represented by a Fuzzy Attributed Relational Graph (FARG) that describes each object in the image, its attributes and spatial relation. The texture and color attributes are computed in a way that model the Human Vision System (HSV) (Aboulmagd et al., 2013). The proposed CBIR system is tested on 400 real images selected from the database (Aboulmagd et al., 2013).Users selects an image from the database that represents the set of images they like to retrieve(Aboulmagd et al., 2013). The user specifies what attributes he mostly would like his search to focus on by assigning weights to each attribute in consideration (Aboulmagd et al., 2013. The proposed system retrieves the ten most similar images based on the user's query with the similarity degree for each retrieved image (Aboulmagd et al., 2013. Each retrieved image is evaluated by three different users i.e. by assigning a mark to each image(Aboulmagd et al., 2013).The proposed CBIR model is only suitable for image retrieval applications that are not precise and require certain user subjectivity (Aboulmagd et al., 2013).Another weakness of the approach is that biasness in part of the users may occur.

Another research (Mukhopadhyay, Dash, & Das Gupta, 2013) implements fuzzy logic. A Content-based texture image retrieval using fuzzy class membership is proposed in which an approach called "Class Membership-based Retrieval" that addresses the limitations of both conventional distance based and conventional classifier based retrieval approaches is proposed (Mukhopadhyay et al., 2013). The proposed model consists of two steps. First, the class label and fuzzy class membership of query image is computed using neural network (Mukhopadhyay et al., 2013).. In the second step, the retrieval is performed using a combination of simple and weighted (class membership based) distance metric in complete search space unlike the conventional classifier based retrieval techniques(Mukhopadhyay et al., 2013). The performance of the method is evaluated using three texture datasets varying in orientations, complexity and number of classes (Mukhopadhyay et al., 2013)The proposed technique also provides flexibility in reducing the search space in steps increasing the speed of retrieval at the cost of gradual reduction in accuracy(Mukhopadhyay et al., 2013).The proposed approach produced a best precision is 60% which means half of the nearly half of query will produce wrong results.

In (Dass, Ali, & Ali, 2014),an image retrieval algorithm using interactive genetic algorithm is proposed. In the paper an approach splitting the retrieval process into two stages is proposed (Dass et al., 2014). In the query stage, the feature descriptors of a query image are extracted and then used to evaluate the similarity between the query image and those images in the database (Dass et al., 2014). In the evolution stage, the most relevant images were retrieved by using the Interactive Genetic Algorithm (IGA) (Dass et al., 2014). IGA is employed to help the users identify the images that are most satisfying to the users' need(Dass et al., 2014). The experimental evaluation of the system is based on a 1000 WANG color image database. The precision rate reported in the research to be 75% which is far much less than many other work on (Mukhopadhyay et al., 2013) and (Aboulmagd et al., 2013).

In (Kavitha & Jeyanthi, 2015),an approach is proposed using Visual Contents & Genetic Approach. The research aims at exploring the efficacious Content Based Image Retrieval technique by feature extraction methods using Color histogram (HSV) and Polar raster (Kavitha & Jeyanthi, 2015).It is then fused using genetic coding and then it Euclidean distance for retrieving the similar images of query for the better retrieval results (Kavitha & Jeyanthi, 2015).The research proposed the efficient CBTR system where all three features of images: color, shape and texture are considered (Kavitha & Jeyanthi, 2015).In the paper, the color histogram features are analyzed based on HSV color space which is used effectively to describe the color features(Kavitha & Jeyanthi, 2015). The shape of image is analyzed by efficient Polar Raster Edge Sampling technique which provides exemplary feature extraction method by binning the counts of the edge points in radial and angular directions to store the feature vectors. The texture is analyzed using FDCT based haralick features which provides high level detailed texture information(Kavitha & Jeyanthi, 2015).Although the paper argue that the results proved that the better retrieval performance obtained for maximum test images based on multi-features compared to single content features(Kavitha & Jeyanthi, 2015),it does not compare the results with any of the single content features. Also, no data set is highlighted in the work thus difficult to know the quality of the experiments and thus the final quality of the model.

A research in (Sugamya, Pabboju, & Babu, 2016) introduces a new two-step strategy in which first step is feature extraction using low level features (color, shape and texture) while SVM classifier is used in the second step to handle the noisy positive examples. Thus, an efficient image retrieval algorithm based on color-correlogram for color feature extraction, wavelet transformation for extracting shape features and Gabor wavelet for texture feature extraction(Sugamya et al., 2016). The dataset used in the experiment is Database of 200 images of 2 different classes is used to check the performance of the algorithm developed. In order to measure retrieval effectiveness for an image retrieval system, precision and recall values are used(Sugamya et al., 2016). Further, multiple features and different distance metrics are combined to obtain image similarity using SVM classifier. Results based on this approach are found encouraging in terms of color, shape and texture image classification accuracy(Sugamya et al., 2016).It can be realized however that the composition of the dataset used has not been used previously by many researcher thus it is difficult to make comparisons (Zhang, Kiranyaz, & Gabbouj, 2017).

In (Lande, Bhanodiya, & Jain, 2014), a content based image retrieval is proposed using color. For extraction of color features, images are divided into non-overlapping blocks, and dominant color of each block is determined using k-means algorithm(Lande et al., 2014). For extracting gray-level co-occurrence matrix (GLCM)-based texture features, each pixel in the image is replaced by average value of its neighborhood pixels. These average values are further quantized into 16 levels, for

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better and efficient representation of texture in the database(Lande et al., 2014). Finally, Fourier descriptors are extracted from the segmented image and are used to represent the shape of objects, as they have better representation capability and robust to noise, than other shape descriptors. The feature vector formed by combining all these is used to represent image in the database(Lande et al., 2014). The proposed approach is tested on wang dataset (Lande et al., 2014).The paper concluded that their approach produced better results but it can be observed that the approach did not show the precision or recall results.

In (Hu, Yin, Han, & Yu, 2014) a similarity image retrieval is proposed for the implementation in E-Commerce. The model proposed includes three components: feature extraction, effective retrieval, and user interface (Hu et al., 2014).The model was implemented using Software Programming: Myeclipse JDK as a system programming language, Macromedia Dreamweaver MX as an interface programming language, NAVICAT Mysql for database and Tomcat 6.0 Web container (Hu et al., 2014).The main functionalities of the model were: Searching similar product image according to information image and Automatically collecting and classifying clothing picture information(Hu et al., 2014). For testing the performance of the model, WANG Dataset of 1000 Images of 10 Categories is used. The experiments results show the following. Average search recall is 59.35%, and the smallest is 40.2%; the average precision is 73.3%, and the smallest is 66.4%. It can be appreciated that the model increased the purchase ratio of customers in E-Commerce site. It can however be observed that a precision of 66.4% is quite low and can result in many customers being unsatisfied in terms of search results.

3. Conclusion

In this paper a review has been conducted and results of various experiments highlighted. We note that majority of the developed model have a precision of less than 0.75.This is a worrying trend as it means that majority of the searches will produce wrong results. However, we do note that Content based Image Retrieval is a promising area as it will replace many challenges including semantic gaps, frustrations of manually annotating many images in a database.

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