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Image Retrieval based on Feature Similarity Score Fusion Using Motley Genetic Algorithm

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Abstract: *In this paper we are proposing an image retrieval method based on feature similarity score fusion using motley genetic Algorithm and chaotic fuzzy logic. Single feature always describes image content onlyin one point of view, which has a certain one-sided effect. System's retrieval performance will improve by fusing multifeature similarity score. In this paper, method of fusing multi-feature similarity score is described by analyzing the retrieval results from colour feature, texture feature and size. For assigning the fusion weights of multi-feature similarity scores reasonably, the motley genetic algorithm using chaotic fuzzy logic is applied.*
Keywords *- content based image retrieval, similarity score fusion, fuzzy logic, fusion weight, chaotic genetic algorithm.*

I. Introduction

In todays world, image retrieval system is a hot topic in digital image processing techniques from data mining community. Digital images are rapidly growing because of developing techniques of multimedia and information [1]. How accurately users can retrieve images of interest is important for digital image databases. Therefore, as an urgent need for various image retrieval applications, advanced search and retrieval tools have been perceived. The text-based image retrieval approaches have been adopted by earliest search engines. The digital images to be mined are either not labelled or annotated using inaccurate keywords because these solutions have shown drastic limitations.. So we can say, text-based retrieval approaches necessitate manual annotation of the whole image collections. However, this tedious manual task is not feasible for large image databases [2].

Content-Based Image Retrieval (CBIR) comes as a promising substitute to surpass the challenges met by text-based image retrieval solutions. Also, digital images, which are obtained using CBIR system, are represented using a set of visual features [3].CBIR system also can be implemented based only on single feature. Single feature of image describes the content from a specific angle. It may be suitable for some images, but it also may be difficult to describe other images [4]. So we can say, describing an image with single feature is incomplete. Representing an image with multi-features from multi-angles is expected to achieve better results[5].

CBIR systems represent an improvement taking advantage of the digital information stored in the image itself when image collections are not semantically annotated with textual labels. Thus, visual features are extracted from images in order to describe its content, and later be compared with the image query [6]. These visual features used in CBIR systems can be classified into low level features (colour, texture and shape) and high level features, which are usually obtained by combining low level features with a predefined model [7]. High level features are not usually suitable for general purpose systems as they have a strong dependency on the application domain, so the extraction of good low level image descriptors in an important research activity in this field. The low level features can easily describe the content of simple images, complex images and high level concepts cannot be properly described. So, this gap between high level concepts closer to human perception and low level features used to describe images is called semantic gap [8], and different methods have been proposed to deal with it. In many cases, the strategies proposed are based on the integration of the information provided by the user into the decision process [9].

The main goal of image retrieval is to retrieve a set of semantically similar images in database based on a query image. This similarity matching can be performed by computing the distance score of the feature descriptors between the query and target images in database. Many methods have been developed for the content-based image retrieval task such as. The image retrieval offers a convenient way to browse and search a set of similar images which can reduce the user time for searching a set of images with similarity and user preference constraints [10].

Most state of the art methods lack the ability to successfully incorporate human intuition into retrieving images [11]. The user wants is a challenge retrieving the image due to the inefficiency in explicit description. In order to supplement the absence of the user competence, we developed automatically detected facial attribute with relevance feedback based face image retrieval [12].

The rest of the paper organization is as follows: Section 2 describes the literature survey and motivation of the work. Section 3 describes describes the problem statement. Section 4 describes the proposed methodology and section 5 we have conclusion. Finally all the references utilized throughout the paper is cited in reference section.

II. Literature Survey

Nishant Shrivastava and Vipin Tyagi [13] have discussed the image retrieval technique which retrieves similar images in three stages. A fixed number of images is first retrieved based on their colour feature similarity. The relevance of the retrieved images is further improved by matching their texture and shape features respectively. This will eliminate the need of fusion and normalization techniques, which are commonly used to calculate similarity scores. This will reduce the computation time and increases the overall accuracy of the system. Also, global and region features are combined in this technique, to obtain better retrieval accuracy. This concept only focused the similarity score assignment based on features not considering the semantics of the image. Accordingly the accuracy of the image retrieval gets low.

Mourão *et al.* [14] presented a medical information retrieval system with support for multimodal medical case-based retrieval. By providing multimodal search, through a novel data fusion algorithm, and term suggestions from a medical thesaurus, the system supports medical information discovery. This algorithm was not be a generic. This method is not provided for the new modality. Ahmad *et al*. [15] discussed an efficient framework to model image contents as an undirected attributed relational graph, exploiting colour, texture, layout, and saliency information. Without requiring any segmentation or clustering procedures, reducing the computational complexity, this method encodes salient features into this rich representative model. Also, an efficient graph-matching procedure implemented on specialized hardware, which makes it more suitable for real-time retrieval applications. This method exploits the local salient maxima. Consequently the computation time was increased.

Memon et al. [16] presented three methods such as1. Geolocation-based image retrieval (GLBIR), 2.Unsupervised feature technique Principal component analysis (PCA) and 3.multiple region-based image retrieval. The first (GLBIR) method identifies geo location an image using visual attention based mechanism and its colour layout descriptors. These features are extracted from geo-location of query image from. This model uses visual metrics for example; the proximity ,colour contrast, size and nearness to image's boundaries to locate viewer's attention which does not fully semantic understanding of image content,. The second method to refine images exploiting and fusing by unsupervised feature technique using principal component analysis (PCA).

A large number of diverse methods have been proposed for CBIR using low level image content like edge, colour and texture. For combination of different types of content, there is a need to train these features with different weights to achieve good results.

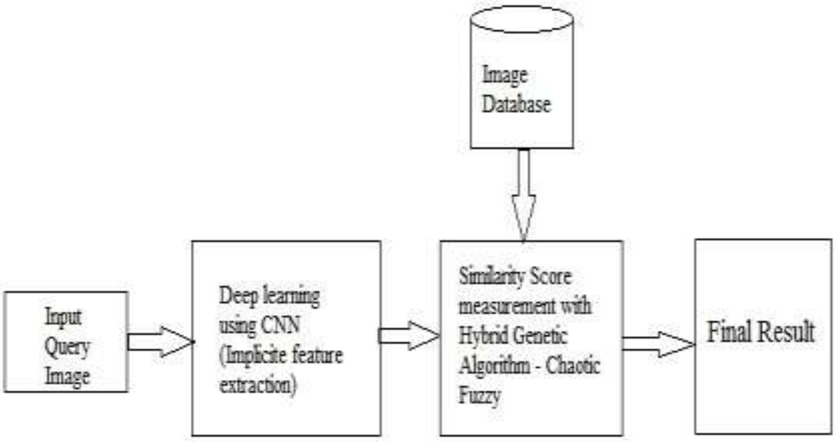
III. Problem Statement

In expensive image-capture and storage technologies have allowed massive collections of digital images to be created in lots of application areas such as medicine, remote-sensing, entertainment, education and on-line information services. Storing of such images is relatively above-board, but accessing and searching image databases are intrinsically difficult and key challenging problems with image retrieval. Image retrieval is done by two ways-1] Text-based approach 2] Content based approach. In text-based approach, image is search through image databases using manual keyword annotations and keyword indexing. Although this approach can be useful, there are two rigorous problems with it. First, textual tagging of images requires a lot of user effort and is also a very tedious task. If the database is very large, then it is not practically feasible to annotate each image with textual tags. Second is that there is no standard vocabulary that is used for textual tagging. The perception of images may vary from person to person, resulting in different tags for images that are otherwise similar. Also the vocabulary that is available may not be sufficient to completely describe the image. Therefore, new ways of indexing, browsing and retrieval of images are needed, which can automatically generate descriptors for images. Content-based image retrieval (CBIR) is a technique in which images are extracted directly based on their visual descriptor such as colour, texture, and edge. An image has several types of features, every features have different effect on image retrieval. How to organize these features and properly assign weights to get satisfying retrieval results is a one of the challenge in CBIR.

IV. Proposed Methodology

Initially input the query image. Then utilize the deep CNN (Convolutional Neural Network) to extract the image feature. In traditional CBIR systems, low-level features such as the colour, shape and texture features are usually extracted to construct a feature vector for describing images and then, images are retrieved by comparing the feature vector corresponding to the query image and those corresponding to images in the data set based on a proper similarity measure. Generally, there are three key issues in CBIR systems, (i) Selecting appropriate feature extraction method, (ii) Extracting appropriate image features. (iii) Matching features with effective method. Many researchers devote most of their attention to the first issue. However, they fail to extract the internal structure contained in the features which is crucial for distinguishing data points. In our paper, from the original data space, we aim to find this internal structure. Moreover, deep learning paradigm is that features need not to be extracted from the raw data beforehand, but the raw data themselves are processed by the network. The CNN also serve as good descriptors for image retrieval. In order to compute the similarity/distance between the images in the database and the query image, the feature vector of query image and feature vector of database images have been compared. The Similarity score fusion is done by the Hybrid GA-Chaotic Fuzzy optimization algorithm. The weight is to be assigned to individual content features. The task of this algorithm consists of finding the weight that maximizes the retrieval accuracy to the context defined by the query image. Here we can have the hybridization with the genetic algorithm, fuzzy c-mean and Improved Glow Worm search optimization. FCM will be terminated once a pre-set convergence criteria is met. Accordingly it can fall prey to local optima problem. In order to avoid this, the Improved Glow worm optimization is incorporated with the FCM. Due to the Chaotic behaviour of Improved Glow worm algorithm the convergence rate will be increased. Furthermore the cross over and mutation step of the genetic algorithm have to be optimized more because of the random searching behaviour. Due to random search we cannot attain the optimal solution. In order to gain that the Chaotic FCM is incorporated to the GA. In accordance with that the optimal similarity score fusion assignment can be made. Depending upon these relevance, similarity between query image and image in data base, final result of images are displayed. This proposed method can be implemented in MATLAB.

Process Flow Diagram



Deep Learning Using Cnn

In order to compute the similarity/distance between the images in the database and the query image, the feature vector of query image and feature vector of database images have been compared. The Similarity score fusion is done by the Hybrid GA-Chaotic Fuzzy optimization algorithm. The weight is to be assigned to individual content features. The task of this algorithm consists of finding the weight that maximizes the retrieval accuracy to the context defined by the query image. Here we can have the hybridization with the genetic algorithm, fuzzy c-mean and Improved Glow Worm search optimization. FCM will be terminated once a pre-set convergence criteria is met. Accordingly it can fall prey to local optima problem. In order to avoid this, the Improved Glow worm optimization is incorporated with the FCM. Due to the Chaotic behaviour of Improved Glow worm algorithm the convergence rate will be increased. Furthermore the cross over and mutation step of the genetic algorithm have to be optimized more because of the random searching behaviour. Due to random search we cannot attain the optimal solution. In order to gain that the Chaotic FCM is incorporated to the GA. In accordance with that the optimal similarity score fusion assignment can be made.

Next, the user gives feedback to the relevance of the initially returned results and submits user feedback to the CBIR system. A relevance feedback algorithm refines the initial retrieval results based on the user's relevance feedback, and returns an improved set of results to the user. The Relevance Feedback Paradigm is employed to improve the retrieval capabilities of CNN by modifying the weights of the similarity features according to the feedback of the user. Typically, to achieve satisfactory results, a number of rounds of users' relevance feedback are needed. Here with the combination of user's feedback (explicit feedback), implicit feedback is also used. That means, here we are using the feedback log with the regular relevance feedback. Log database is used to collect and store user’s relevance feedback. When feedback log data is unavailable, the log-based relevance feedback algorithm behaves exactly like a regular relevance feedback algorithm we need to systematically organize the log data of users' feedback. Assume a user labels N images in each round of regular relevance feedback, which is called a log session. Thus, each log session contains N evaluated images that are marked as either "relevant" or "irrelevant." System accept explicit and implicit feedback and sends the explicit feedback to the retrieval system and at the same time sends the implicit feedback to the log session. Then sends the processed data to log database. Depending upon these relevance feedback recomputed similarity between query image and image in data base. System is terminated when user is satisfied with retrieval result.

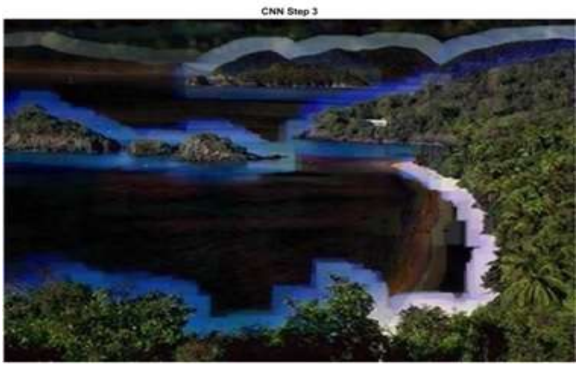
V. Result

Input Image

CNN Step 1

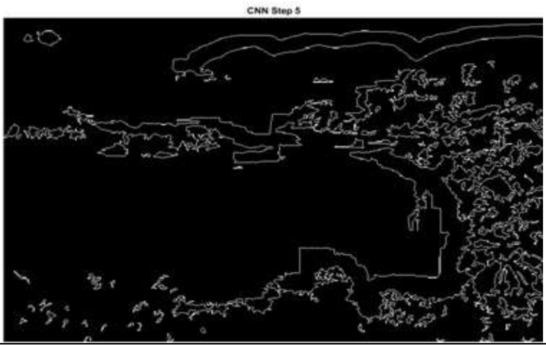
CNN Step 2

CNN Step 3



CNN Step 4

CNN Step 5



Output Images

VI. Conclusion

CBIR is a process to look for the applicable picture in photograph database when a question photo is given through the user. In this paper, we used colour, texture, and shape capabilities to classify the question photograph with Convolution Neural Network (CNN) for feature extraction. Then using Motley Genetic Algorithm, similar images with reference to question image are found from the photograph database. For simulation purpose, we have used MATLAB software,

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References

[1]. Suresh, M. B., and B. Mohankumar Naik. "*An Efficient Approach of Content Based Image Retrieval using Texture, Colour and Shape Features of an Image*". International Journal of Engineering Trends and Technology (IJETT), Volume-48 Number-6, 2017.

[2]. Wang, Xiang-Yang, Bei-Bei Zhang, and Hong-Ying Yang. "*Content-based image retrieval by integrating colour and texture features*." Multimedia tools and applications 68, no. 3 (2014): 545-569.

[3]. Ismail, Mohamed Maher Ben. "*A Survey on Content-based Image Retrieval*." (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 8, No. 5, 2017.

[4]. Ligade, Anita Nanasaheb, and Manisha R. Patil. "*Optimized Content Based Image Retrieval Using Genetic Algorithm with Relevance Feedback Technique*." International Journal of Computer Science Engineering and Information Technology Research (IJCSEITR) (2013): 49-54.

[5]. Chen, Mianshu, Yuan Sun, Ping Fu, and Hui Zhang. "*Image retrieval based on multi-feature similarity score fusion using genetic algorithm*." In Computer and Automation Engineering (ICCAE), 2010 the 2nd International Conference on, vol. 2, pp. 45-49. IEEE, 2010.

[6]. Hu, Mengqiu, Yang, Fumin Shen, Luming Zhang, Heng Tao Shen, and Xuelong Li. "*Robust web image annotation via exploring multi-facet and structural knowledge*." IEEE Transactions on Image Processing 26, no. 10 (2017): 4871-4884.

[7]. de Ves, Esther, Xaro Benavent, Inmacula Coma, and Guillermo Ayala. "*A novel dynamic multi-model relevance feedback procedure for content-based image retrieval.*" Neuro computing 208 (2016): 99-107.

[8]. Suchitra, S., S. Chitrakala, and R. Sivaranjani. "*An Enhanced Face Image Retrieval using Relevance Feedback*." International Journal of Applied Engineering Research 10, no. 17 (2015): 2015.

[9]. Poslad, Stefan, and Kraisak Kesorn. "*A Multi-Modal Incompleteness Ontology model (MMIO) to enhance information fusion for image retrieval*." Information Fusion 20 (2014): 225-241.

[10]. Liu, Peizhong, Jing-Ming Guo, Kosin Chamnongthai, and Heri Prasetyo. "*Fusion of color histogram and LBP-based features for texture image retrieval and classification*." Information Sciences 390 (2017): 95-111.

[11]. Karthik, P. Suman, and C. V. Jawahar. "*Analysis of relevance feedback in content based image retrieval*." In Control, Automation, Robotics and Vision, 2006. ICARCV'06. 9th International Conference on, pp. 1-6. IEEE, 2006.

[12]. Dureja, Aman, and Payal Pahwa. "*Image retrieval techniques: a survey*." International Journal of Engineering & Technology 7, no. 1.2 (2018): 215-219.

[13]. Shrivastava, Nishant, and Vipin Tyagi. "*An efficient technique for retrieval of color images in large databases*." Computers & Electrical Engineering 46 (2015): 314-327.

[14]. Mourão, André, Flávio Martins, and João Magalhães. "*Multimodal medical information retrieval with unsupervised rank fusion*." Computerized Medical Imaging and Graphics 39 (2015): 35-45.

[15]. Ahmad, Jamil, Muhammad Sajjad, Irfan Mehmood, Seungmin Rho, and Sung Wook Baik. "*Saliency-weighted graphs for efficient visual content description and their applications in real-time image retrieval systems*." Journal of Real-Time Image Processing 13, no. 3 (2017): 431-447.

[16]. Memon, Muhammad Hammad, Jian-Ping Li, Imran Memon, and Qasim Ali Arain. "*GEO matching regions: multiple regions of interests using content based image retrieval based on relative locations*." Multimedia Tools and Applications 76, no. 14 (2017): 15377-15411.