A HOMOGENEOUS SEMANTIC IMAGE RETRIEVAL USING RELEVANCE BASED WEIGHT ADJUSTMENT TECHNIQUE

[1]Ms.N.N.Deepika , [2]Dr.R.Madhumitha
[1]UG Student,[2]Assistant Professor
Department of Computer Science and Engineering
Sri Krishna College of Engineering and Technology,Coimbatore, India
[1]15epcs006@skcet.ac.in,[2]madhumitha@skcet.ac.in

Abstract- SBIR is a semantic gap between the high-level image and the low-level image. In other words, there is a difference between what image features can distinguish and what people perceives from the image. Semantic Image retrieval is the most complex process in the real time scenario where the similarity finding would be more difficult in case of larger homogeneous image contents. This paper proposes a fuzzy logic based feedback weight adjustment scheme which will increase the score of the class which is more preferred by the users. Through theoreticalanalysis and extensive result, it is shown that our weight adjustment scheme algorithm provides significant performance improvement in terms of high retrieval precision and good user satisfaction level.

Keywords- SBIR, Hadoop,Hbase, Mapreduce function.

I. INTRODUCTION

Nowadays, huge volumes of digital images are being generated and consumed daily. With the development of Internet technology,the number of digital image contents has exploded. Currently,digital image makes up 60% of Internet traffic, 70% of mobile phone traffic, and 70% of all available unstructured data [1]. Image retrieval has become a form of big data which gives the users valuable information such as event occurrence, network computing, purchase recommendation and workflow control [2]. Therefore,image content retrieval of big data theenvironment is spurring on a tremendous amount of research [3]. Digital image big data retrieval has its own particularities. In this paradigm, homogeneous image computing has switched into a distributed pattern to store and process the massive amount of contents. Although this manner alleviates the maintenance and the computing burden of the client, homogeneous image big data storage and processing are facing great challenges. In big data environment, a huge number of commodity computers, which possess massive compute power and storage quality will generate homogeneous content. Since lot of services and applications will provide, edit, process, and retrieve rich similar image contents, often express similar semantic information.In the image retrieval process,the user's intent is another critical issue. In some traditional approaches, the retrieval is usually restricted to the same type ofimages. This constraint reduces the QoS of homogeneous image retrieval because the returned analysis may fail to identify users' search intent due to the shortage of type diversity. Therefore, it becomes a significant issue to solve type heterogeneity, storage, distribution and auser's intent for a good retrieval performance and economic efficiency [4].

The characteristics of SBIR are as follows:

(1) ***Homogeneous image retrieval***, because any type of images can be uploaded and retrieved;
(2) ***Convenience***, since a familiar retrieval interface similar to traditional commercial search engines;
(3) ***Reduced I/O cost***, as store the ontology and act as semantic information in the database, then provide links to the real image, directly process with large size.
(4) ***Economic efficiency***, as low-end computers together with open-source frameworks are used to store NoSQL database and process the retrieval, respectively.

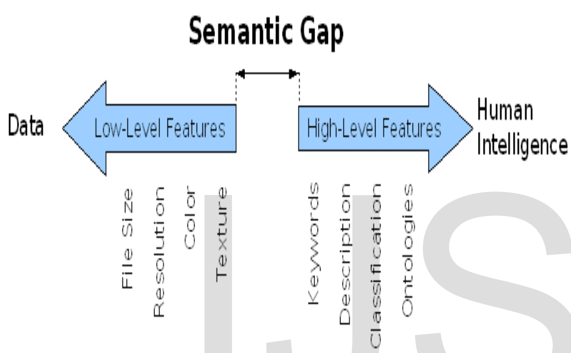

Fig 1: Architecture of SBIR

Fig. 1 shows the features and communications with a typical SBIR. The summary of the related work of Semantic Based Image Retrieval is elaborated in section II. This is followed by a brief description of our proposedarchitecture, including semantic extraction and representation,semantic storage, homogeneous image retrieval algorithm and user feedback in section III. Then provide the performance evaluation and experimental result in section IV. Concludes with suggesting the extension of proposed work in section v.

II. RELATED WORK

In the past decades, image retrieval is mainly founded on text-based approaches, which are solely based on the text contents surrounding homogeneous image in certain host files. Although keywords are utilized to retrieve various types of image retrieval, this method is not intrinsically homogeneous supported. The retrieval is not able to achieve an excellent performance because of the noise[5,6]. Regardless of the fact that users feel more convenient to retrieve image content through text keywords, content-based retrieval has been widely used in commercial search engines, such as Google and Bing Image Search. However, it is extremely difficult to acute image retrieval based on homogeneous content [7,8]. For instance, given an imagedocuments for the same artist, the content-based approaches haveno strength to identify the artist or extract other similar features of the binary data of the two documents because of the data formatsdifference. Thus, in many cases, content-based approach may avoid the users' retrieval intent.To support the users' intent reflected retrieval, some contributionsfocused on introducing relevance feedback (RF) in content-basedretrieval(CBIR). Comprehensive surveys for RF in image retrieval systemswere presented in [9]. Representative contributionsinclude active learning algorithm for conducting effective relevancefeedback [10], Support Vector Machines (SVMs) based feedbackanalysis [11], local geometrical graph based feedbacklearning [12] and Biased Discriminant Analysis (BDA)approach [13]. However, themain drawback of RF is toincrease user involvement. Query users are expected to provide onlylimited feedback, and excessive feedbacks will increase their burden[9]. In recent years, some contributions is to support homogeneous image retrieval have been proposed. For text-image retrieval,[14]modelled the correlations between text and image modalities and observe them with canonical correlation analysis. In 2014, this approach was revised to achieve a better performance [15],andproposed a homogeneous media similarity measure with nearest neighbours which considers both intra-media and inter-

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media correlations. Reported accumulated reconstruction error vector to combine the original feature descriptions into a shared semantic space. However, these approaches only support the homogeneous retrieval between image and text documents. In bigdata environments, information retrieval encounters some specific problems such as the data complexity, uncertainty and emergence. Traditional RDBMS (Relational Database Management System) technology is not able to satisfy the requirement of homogeneous information retrieval due to the data variety and thehigh investment [7]. At present, NoSQL technology is useful to store the information which can be represented as map format. Apache HBase is a typical database to analysis the NoSQL idea, which simplifies the design, horizontal scaling and finer control over availability. The features of HBase are outlined in the original work of GoogleFileSystem and Big Table. In HBase, tables serve as the input and output for MapReducejobs running in Hadoop [17], andmay be accessed through certain typical APIs, such as Java [17].

III. PROPOSED SBIR ARCHITECTURE

Semantic based Image Retrievaluses inexpensive investment to store and retrieve semantic information. In this architecture, homogeneous image with large size is not directly processed, HBase only stores ontology act as semantic information which can be parallel processed in distributed nodes with MapReduce-based retrieval algorithm. The experimental results show that SHMR can effectively identify the homogeneous image. The image content will be obtained from various sources such as Web crawling, sensor collection and user generating.

The semantic information will be initialized by two ways:

□ **Social annotating,** which means extracting semantic information from annotations provided by social users.

□ **Automatic learning,** which denotes analysing semantic information from multimedia features using topic models.

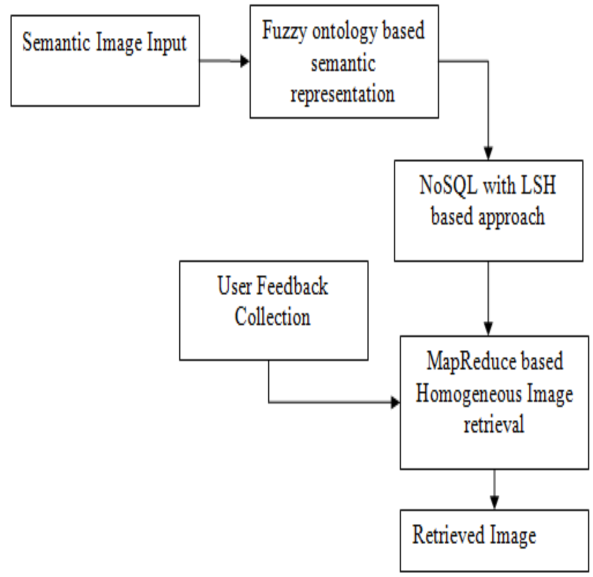

Fig 2: The proposed SBIR Architecture

After the semantic extraction, the semantic fields together with the image location will be represented by ontology as shown in fig 2. Weight adjustment scheme is employed to adjust the weight of every semantic field. Ontology files are saved into HBase linked to the real data with the location information. For better adaptation to NoSQL-based big data processing tool, use the map<key, value> structure conversion process to normalize the correspondence between image location and semantic fields. Next, the index and storage block will be generated, according to which the ontology will be saved into the NoSQL-based distributed semantic database managed by HBase.

Users can upload annotated image with arbitrary format to execute the homogeneous image retrieval. The semantic information of the uploaded file(s) is extracted by social annotating and automatic learning. Then the engine will execute the ontology generating and map structure conversion to adapt to MapReduce-based retrieval. After the retrieval, the engine will return the results as the thumbnails with the file locations.

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Finally, social userswill be asked to give additional annotations to the image and they selected to make annotations more abundant and accurate.

IV. WEIGHT ADJUSTMENT SCHEME ALGORITHM

In the proposed method, fuzzy ontology classification based relevance feedback system is introduced for the improved user satisfaction level. This is done by considering the increasing the weight value of the contents in terms of user preference value. Much work regards the relevance feedback problem as a strict two-class classification problem, with equal treatments on both positive and negative examples. It is reasonable to assume positive examples to cluster in particular way (maybe non-linearly), but negative examples usually do not cluster since they can belong to any class. Forcefully assuming all negative examples into one class can mislead the algorithm therefore hurt the robustness in performance, especially when the number of training samples is small.

A. WEIGHT ADJUSTMENT SCHEME BASED ON FUZZY RULES ALGORITHM:

Algorithm:

Input: Define matrix S_{mi} for every input image I_i, define semantic matrix S.

Step 1: Initialize:

1. Obtain the semantic fields and store them to S_{mi}.
2. Assign w_i in S_{mi} as 1/n.
3. Combine all the S_{mi} to generate semantic matrix S.

Step 2: Adjustment during Retrieval:

1. Set step = 1
2. For each returned document M
3. For j = 1 to n
4. If M_i is retrieved by s_j Then
5. set $k_j = 1$
6. Else set $k_j = 0$
7. End If
8. Compute the frequency of occurrence of the image tf_{ik} in database.
9. Weight of image i in s_j is $w_{ik} = tf_{ik} \times idf_j$ //$idf_j = \log(N/n_k + 0.01)$
10. Compute the term weight

$$w_{ik} = \frac{w_{ik}}{\sqrt{\sum_{i=1}^{m} (w_i)^2}}$$

11. End For
12. End For

Output: Restore all the adjusted semantic matrices to generate new matrix S.

During an image retrieval database process, it is reasonable to ask the user to click to indicate what he/she assume are relevant or irrelevant to the target image/class in his/her mind—for example, which are “horses” and which are not. But it would be very unnatural to ask the user to also select the class membership of those irrelevant images. So a typical relevance feedback process is a biased classification problem.

V. EXPERIMENTAL EVALUATIONS

In this experiment, we firstly testify the effectiveness of our algorithm and upload a sample homogeneous image. Trained Semantic Image Retrieval (SIR) and built the ontology concepts using 90 images which contain pictures of 20 different humans. Partial training dataset is shown in fig 3. We have evaluated SIR on large number of test cases results were promising and showed the efficiency of the proposed system. In this section, few of the test cases are presented and discussed in detail and search the homogeneous image similar to it. The time cost includes extracting semantic

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information from documents and matching the semantic fields in HBase.

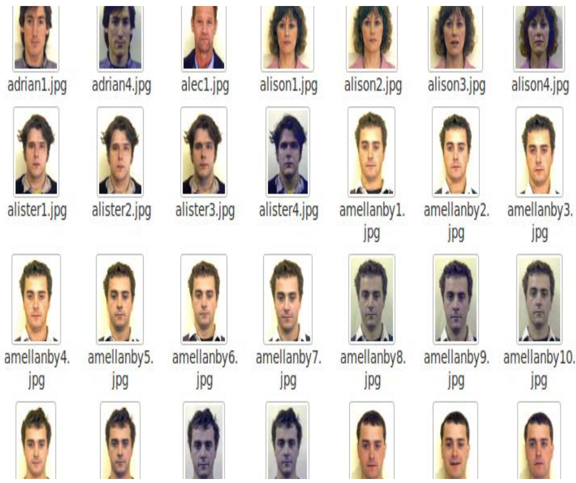

Fig 3: Partial Training set

A. GRAPHICAL ANALYSIS

i. Test Cases(x) vs. Accuracy(y):

Fig 4 shows the accuracy comparison of color based shape based, texture based and our proposed approach with reference to two different test cases. As depicted by fig 4, our proposed approach out performs these approaches with reference to accuracy.

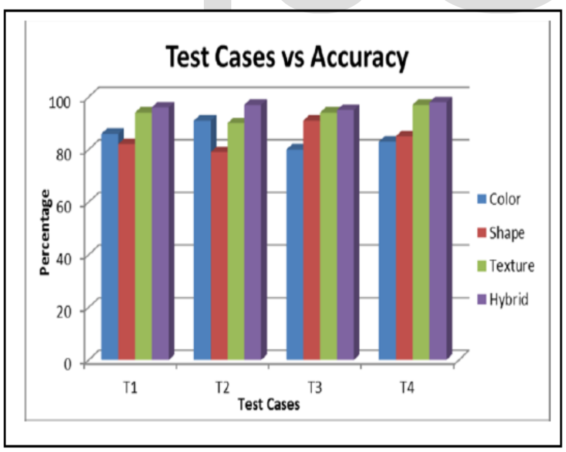

Fig 4: Test Cases(x) vs. Accuracy(y)

ii. Test Cases(x)vs. Percentage(y)

Figure 5 shows the percentage improvement of proposed technique over number of test cases; as shown in figure 5 the proposed solution improvement percentage varies over number of test cases, this is because the content of images present in each test case plays an important role.

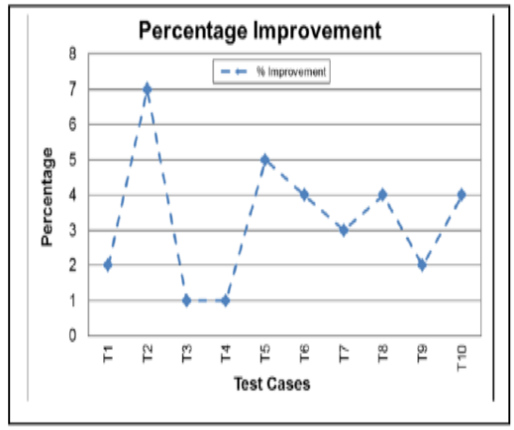

Fig 5:Percentage(y) vs. Test Cases(x)

iii. Test Cases(x) vs.False Positive Percentage(y)

Fig 6 shows false positive percentage over number of test cases, the proposed solution false positive percentage ranges from 0.60 to 2 percent in the test cases which shows the result accuracy of the proposed solution.

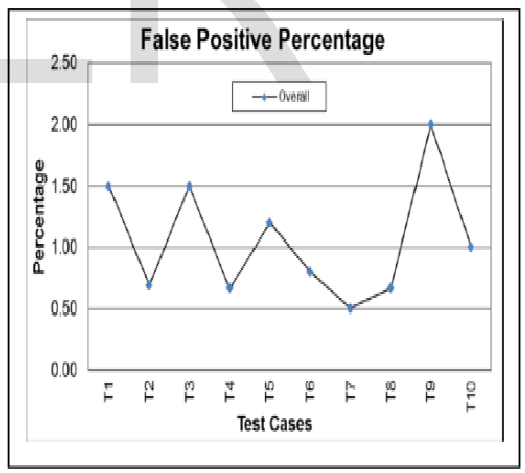

Fig 6: False Positive Percentage vs. Test Cases

In fig 7, the user used andrioimage as input; Query Engine generates the query for the same and executes it on ontology knowledge base. The resultant images are found in the knowledge base, therefore web image search, image filtration and ontology updating steps are skipped in this test case.

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Fig 7: Test case 1

The results are passed to Ranking Module which ranks the results and displayed it to the user as shown in Fig 8. Fig 8 are similar to the first test case (fig 7) where the user enters an image and relevant images are returned to the user.

Fig 8: Test Case 2

VI. CONCLUSION

In this project, a novel architecture called SBIR (semantic-based image retrieval) supporting the semantic image retrieval in homogeneous big data environments has been proposed. The semantic fields extraction, data storage, semantic-based image retrieval and performance evaluation model are described. Algorithms proposed in this project are utilized for solving the weighted adjustment during the retrieval process. Initially, noises in semantic information cannot reflect user's intent, how to eliminate them to guarantee better retrieval precision. Second, given the image documents with semantic information, how to convert it to map structure and retrieve it from the database.

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