ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 1, Issue 6, August 2012

Memory Learning Framework for Retrieval of Neural Objects

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Abstract: Most current content-based image retrieval systems are still incapable of providing users with their desired results. The major difficulty lies in the gap between low-level image features and high-level image semantics. To address the problem, this study reports a framework for effective image retrieval by employing a novel idea of memory learning. It forms a knowledge memory model to store the semantic information by simply accumulating user-provided interactions. A learning strategy is then applied to predict the semantic relationships among images according to the memorized knowledge. Image queries are finally performed based on a seamless combination of low-level features and learned semantics. One important advantage of our framework is its ability to efficiently annotate images and also propagate the keyword annotation from the labeled images to unlabeled images. The presented algorithm has been integrated into a practical image retrieval system. Experiments on a collection of large number of images demonstrate the effectiveness of the proposed framework.

***Keywords*—** CBIR, Image Retrieval, Relevance Feedback, Image authoritative rank, Memory Learning Framework, Feature Extraction

I. INTRODUCTION

"Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases". Image retrieval is the process of browsing, searching and retrieving images from a large database of digital images. The collection of images in the web are growing larger and becoming more diverse .Retrieving images from such large collections is a challenging problem.

One of the main problems they highlighted was the difficulty of locating a desired image in a large and varied collection. While it is perfectly possible to identify a desired image from a small collection simply by browsing, more effective techniques are needed with collections containing thousands of items.

To search for images, a user may provide query terms such as keyword, image file/link, or click on some image, and the system will return images "similar" to the query. The similarity used for search criteria could be Meta tags, color distribution in images, etc. Unfortunately, image retrieval systems have not kept pace with the collections they are searching. The shortcomings of these systems are due both to the image representations they use and to their methods of accessing those representations to find images.

A. Overview of Content Based Image Retrieval

In recent years, with large scale storing of images the need to have an efficient method of image searching and retrieval has increased. It can simplify many tasks in many application areas such as biomedicine, forensics, artificial intelligence, military, education, web image searching. Most of the image retrieval systems present today are text-based, in which images are manually annotated by text-based keywords and when we query by a keyword, instead of looking into the contents of the image, this system matches the query to the keywords present in the database.

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Earlier Image searching done by the technique called Image Meta search. Image Meta search is a searching technique that searches the images based on the Image Meta data such as text, keywords etc. Due to the rapidly growing amount of digital image data on the Internet and in digital libraries, there is a great need for large image database management and effective image retrieval tools. Content-based image retrieval (CBIR) is the set of techniques for searching for similar images from an image database using automatically extracted image features.

Tremendous research has been devoted to CBIR and a variety of solutions have been proposed within the past ten years. By and large, research activities in CBIR have progressed in three major directions:

- Global features based.
- Object/region-level features based.
- Relevance feedback.

All web search engines leaders, such as Google, Yahoo, Ask and etc., find multimedia content by means of text descriptions. Billions of images are tagged manually by

ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
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keywords, so we have got used to search multimedia files by text queries.

But this approach has two cardinal and critical drawbacks:

- Text descriptions are very subjective and therefore far from perfection, the same image can be depicted by absolutely opposite keywords;
- Tagging multimedia files is very hard, time-taking and staff-resources-taking work.

We consider RF from the perspective of supervised learning. Given a query, the system first retrieves a list of ranked images using a similarity metric. Then, the user selects a set of positive and negative examples from the returned results. The systems learn from labeled examples to train a classifier. Many classical machine learning schemes may be applied to train the classifier, such as Bayesian learning, Support Vector Machines (SVM), Boosting, and so on. The retrieval performance is gradually improved after several feedback iterations. The step procedure follows as shown in below figure Initially Feature extraction does for every image in a database and stores. Once we input the image as query image then the feature extraction does for that query image also. Then the matching of features takes place for searching of image.

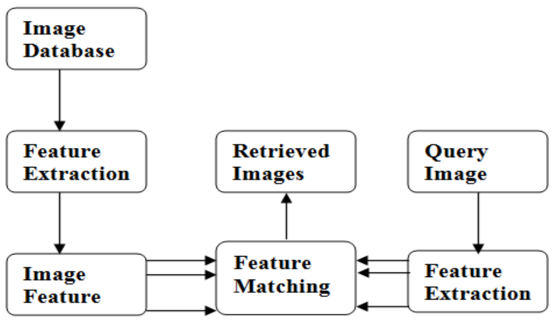

Figure 1: Processing steps for CBIR

After RF for CBIR was first proposed by Rui et al., this area of research has attracted much attention and become active in the CBIR community. Recently, many researchers began to consider the RF as a learning or classification problem. That is, a user provides positive and/or negative examples, and the systems learn from such examples to refine the retrieval results or train a classifier by the labeled examples to separate all data into relevant and irrelevant groups. Although RF can significantly improve the retrieval performance, its applicability still suffers from three inherent drawbacks.

i. Incapability of capturing semantics.
ii. Scarcity and imbalance of feedback examples.
iii. Lack of the memory mechanism.

II. PREVIOUS WORKS

The paper named “A Memory Learning Framework For Effective Image Retrieval” by, Junwei Han, King n. Ngan, Mingjing li, and Hong-Jiang Zhang was published in the year 2005. This gave the idea that a framework can be used in which the features of the images extracted can be stored and used later for faster access and hence improves the response time.

In reference [6], the paper proposes a relevance feedback based interactive retrieval approach, which effectively takes into account two characteristics in CBIR. During the retrieval process, the user's high-level query and perception subjectivity are captured by dynamically updated weights based on the user's feedback.

Automatic linguistic indexing of pictures is an important but highly challenging problem for researchers in computer vision and content-based image retrieval. In reference [7], the paper introduces a statistical modeling approach to this problem. Categorized images are used to train a dictionary of hundreds of statistical models each representing a concept. Images of any given concept are regarded as instances of a stochastic process that characterizes the concept.

The reference [8], discusses a general active learning framework for content-based information retrieval (CBIR). It uses this framework to guide hidden annotations in order to improve the retrieval performance. For each object in the database, it maintains a list of probabilities, each indicating the probability of this object having one of the attributes.

The reference [9], says that Region of Interest (ROI) plays an important role in image analysis. In this paper, an efficient approach for content based image retrieval combining both color and texture features using three ROIs was proposed. Firstly, segment image to three parts using K-means algorithm. Secondly, select three ROIs from the three parts and then extract color features and texture features of ROIs.

III. CONTENT BASED IMAGE RETRIEVAL

A. CBIR Techniques

Many CBIR systems have been developed, but the problem of retrieving images on the basis of their pixel content remains largely unsolved. Different implementations of CBIR make use of different types of user queries. Query by example is a query technique that involves providing the CBIR system with an example image that it will then base its search upon. The underlying search algorithms may vary depending on the application, but result images should all share common elements with the provided example. Options for providing example images to the system include:

- A preexisting image may be supplied by the user or chosen from a random set.
- The user draws a rough approximation of the image they are looking for, for example with blobs of color or general shapes.

This query technique removes the difficulties that can arise when trying to describe images with words.

B. Medical Diagnosis

It is well acknowledged that medical image databases are a key component in diagnosis and preventive

ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 1, Issue 6, August 2012

medicine. There is an increasing trend towards the digitization of medical imagery and the formation of adequate archives. The resulting picture archiving and communication systems (PACS) are available across wards within a hospital setting and allow global access to shared resources. Although a PACS relies on complex protocols such as digital imaging and communication in medicine (DICOM), image selection within a DICOM network is based currently on alphanumerical information only. However, information contained in medical images differs considerably from that residing in alphanumerical format.

The increasing reliance of modern medicine on diagnostic techniques such as radiology, histopathology, and computerized tomography has resulted in an explosion in the number and importance of medical images now stored by most hospitals. While the prime requirement for medical imaging systems is to be able to display images relating to a named patient, there is increasing interest in the use of CBIR techniques to aid diagnosis by identifying similar past cases.

IV. SYSTEM DESIGN

The key assumption of the proposed model is that two images share similar semantics if they are jointly labeled as positive examples in a query session. Intuitively, we can estimate the semantic correlation between two images by means of the number of query sessions in which both images are positive examples. A query session contains a query phase and possibly several rounds of feedback. For the sake of simplicity, the number of times that two images are jointly relevant to the same query is referred to as the co-positive-feedback frequency, while that when both are labeled as feedback images and at least one of them is positive is referred to as co-feedback frequency.

Consequently, the correlation strength between two images is defined as the ratio between their co-positive-feedback frequency and their co-feedback frequency. According to this definition, the correlation value is within the interval between 0 and 1. The larger the correlation is, the more likely that these two images are semantically similar to each other. If two images are never marked as the positive example together in a single query session, their correlation value is zero. It is important to note that the proposed model does not assume any correlation between two negative examples because they may be irrelevant to the user's query in many different ways.

A. Design Modules

Design phase is considered as the most important stage in the project development. This phase was carried out through following stages.

- Image Querying Module
- Feature Extraction Module
- Image authoritative rank
- Hidden Semantic Correlation Between two images Module
- Hidden Semantic Correlation Between an image and Feedback
- Retrieval Module

i. Image Querying Module:

Large number of images is required to ensure proper training of the knowledge base. The extracted features of the fish are used after normalization to train the developed Model. Image Querying Module We are passing the image in the form of query to the subsystem for extracting the features.

ii. Feature Extraction Module

Feature extraction module is heart of the system. It extracts the feature vectors from the images present in the database and query image that is given through querying module. The features like both local and global (low-level and high-level) features are extracted.

The extracted feature vectors are stored into another database called as Meta database. Clustering module is used for efficiently organizing feature vector for faster retrieval of images. Querying Module is used by the user for retrieving image from image database. Finally the Retrieval module comes into picture and it gives the retrieved images to the user. The brief over of operation is as shown in figure.

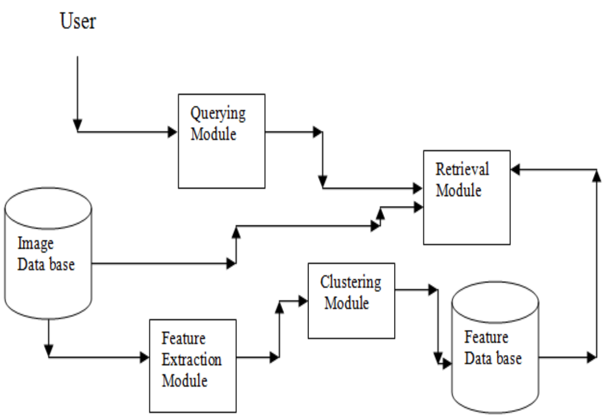

Figure 2: Feature Extraction processing steps

iii. Image authoritative rank

The image authoritative ranks reflect how likely images contain their associated semantic topic. The direct link number of one image measures how many images this image has the direct link with in its semantic class.

iv. Hidden Semantic Correlation Between two images Module

We first introduce the definition of semantic similarity between two clusters that will be used to estimate the hidden semantic correlation between two images. Intuitively, for two different clusters, stronger semantic links between them indicate that they are more semantically similar. Hence, the sum of semantic correlations between members of two clusters could be used as the similarity measure. However, a regular similarity should be within the range of [0, 1].

v. Hidden Semantic Correlation Between an image and Feedback Module.

During a query session, after the user provides a set of feedback examples, there emerges a question. If an image

ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
Volume 1, Issue 6, August 2012

of database has no "direct link" to any of the feedback examples, how to determine the correlation degree between this image and the feedback example set? To address this problem, in this subsection, a probabilistic approach is suggested to approximate the hidden semantic correlation between an image and the feedback examples. Only positive examples are used in the probabilistic approach.

vi. Retrieval Module.

Retrieves the Final Answer with Extracted Result Image and Feedback Images. The searched results, accurate and feedback images. Also gives alert message if image is not present in database.

B. Architecture description:

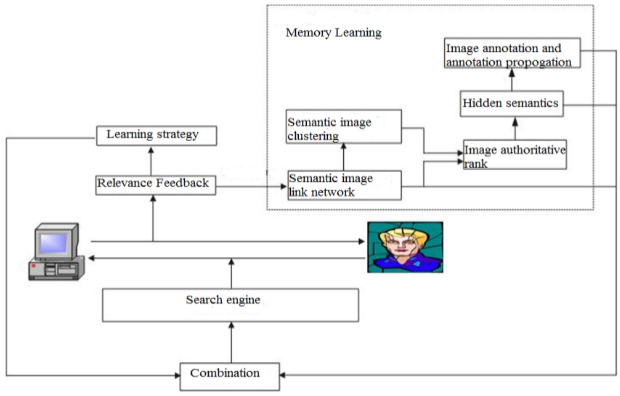

Figure 3: Memory Learning framework Architeture

Search engine will start the searching process. Relevance Feedback will collects the feedback results based on low-level features. Memory Learning will contain high-level features of image.

Semantic image link network describes the images having links to other images in database. It is a simple graphical representation. The link intensity on each individual link stands for the degree of semantic relevance between two images. Hence, the link intensity is assigned to its corresponding semantic correlation.

In the network, we say there is a "direct link" between two images if semantic correlation between those is greater than 0, otherwise, we say there is no "direct link" between them.

Clustering module is used for efficiently organizing feature vector for faster retrieval of images.Semantic image clustering will groups the images together based on semantic relation between images. Every cluster resembles the semantic cluster or semantic correlation between each and every image in a cluster.

Image authoritative rank describes how likely the image contains the specific concept in cluster. An image with strong links to images of its same cluster but with weak links to images of other clusters always has the high authoritative rank. The larger the authoritative rank of an image is, the more likely that this image can represent the corresponding concepts of its cluster.

Hidden Semantics is semantic relation between images with no direct link. The sum of semantic correlations between members of two clusters could be used as the similarity measure. Image annotation is given for initial image and propagated to other un-annotated images. Basically, there are two major issues in annotating image and propagating keywords: which subset of images should be initially labeled and which probability should be used to propagate keywords from one annotated image to one unannotated image.

Learning strategy is for learning both semantic and hidden semantics of images. Once all data is collected the scanning or searching process is done in Visual feature database for the visual feature of query image.

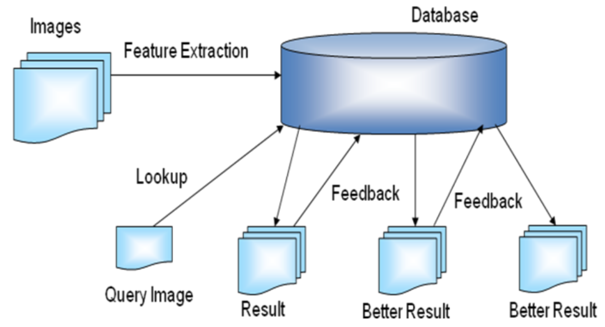

Figure 4: Block Diagram of a system with Feedback

When a query session starts the searching is done in feedback knowledge memory at the beginning if present then the result is displayed, if not then it goes to the actual database images to search for query image. Once the image is found by searching, it is displayed. With that there may be given number of images which are relevant to resultant image are also displayed.

User may mark those as feedback examples and store in feedback knowledge memory for future reference. If the query image is not matched with any images in database then the alert message given as image not found.

C. Step Procedure of Operation:

The same steps are carried out for images in database and also the query image.

i. Database side and Query Image Side

a) Preprocessing: Is the process where the connection establishment to database is done. All images in all folders of database are retrieved. No other files are retrieved other than the images in a database.

b) Segmentation: Before the feature extraction is done for an image every image should be segmented into many regions or objects of equal size. The segmentation process will start at the right-top corner of an image. Segmentation is done for every image retrieved individually for a fixed size of pixel of image.

c) Feature Extraction: The Feature extraction is done for every pixel or object of an image. Feature extraction considers both the local and global features of an image.

ISSN: 2278 – 1323
International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)
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Once the features are extracted, they are stored in a separate table of database called the visual features table. The visual features are in the form of numbers, i.e. numerical representation of an each pixel or segment of an image.

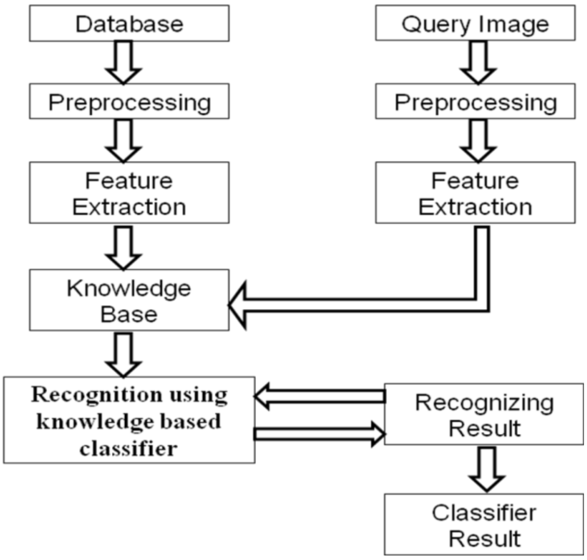

Figure 5: Processing steps for Memory Learning Framework

ii. Similarity Checking:

d) Knowledge Base: Is a memory that stores all the visual features of both images of database and the query image.

e) Recognition using knowledge based classifier: The searching or the scanning process is took place here. The visual features of images of database are searched for the visual features of query image by using the linear search technique.

Here the feedback comes into play, where the user can give feedback on the displayed images and match the ones which are closest match to the query image.

f) Classifier result: Classifies the result based on the recognition done. Classifies the image to give the result as accurate image, feedback image or image not found.

g) Recognize result: Recognize and displays the result what the classifier gives.

V. IMPLEMENTATION

A retrieved image is considered to be relevant if it belongs to the same category of the query. In all experiments, we determine the weights by the Rui's reweighting algorithm. The value of the image class number k is predefined to the category number of the image database used in the experiment.

The retrieval accuracy is defined as:

$$\text{Accuracy} = \frac{\text{relevant images retrieved in top T returns}}{T}$$

To build feedback knowledge memory model, eight real-world users to retrieve images using the system. Each one of seven users was required to perform 200 query sessions, and the last user provided 100 query sessions. Each query session consisted of four iterations of feedback. At each iteration, the users marked positive and negative examples according to their preferences.

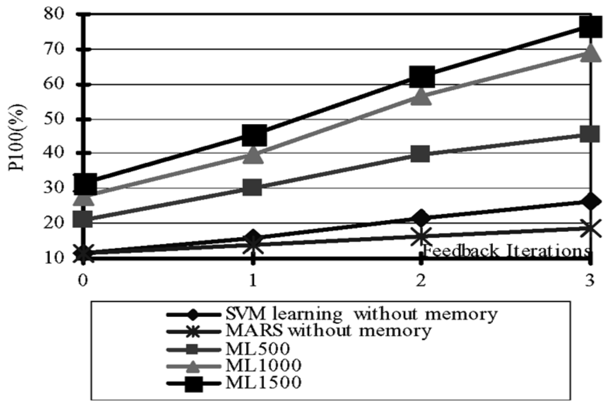

Figure 6: Performance comparison between memory learning framework and non memory RF.

To test the effectiveness of the proposed framework, we compared its retrieval performance with two classic non memory approaches: SVM learning-based RF and MARS. To show the effect of the amount of memorized knowledge, 1 500 queries were used in three stages: ML500 using 500 queries, ML1000 using 1000 queries, and ML1500 using 1500 queries. Figure 3 presents the experimental results. Clearly, the proposed framework improves the retrieval accuracy substantially. Moreover, the more memorized feedback information from the users' interactions, the better the performance of the retrieval system.

We did 15 wrong query sessions to simulate the user errors (here, user errors mean images labeled as positive examples are not in the same category of the query image), and then merged them into those 150 real-world user log. In this way, the simulated user error rate is around 10%. Under the simulated noisy environment, we tested the retrieval performance of the proposed system again. As can be seen from Figure 5, the proposed system enjoys little performance degradation under this simulated noisy environment. This experiment demonstrates that the memory learning framework is robust to mild user errors.

In the proposed framework, the traditional RF and memory learning are not a purely linear combination. The memory learning can automatically provide additional positive examples to the traditional RF. More specifically, given a query session, after the user offers feedback examples, images of database with the large semantic correlation to any one of positive examples are also automatically regarded as positive examples. We argue this "help" can alleviate the limitation of scarcity and imbalance of feedback examples. An experiment was designed to examine this "help." This experiment used the two traditional RF algorithms: SVM learning and MARS.

We compared the performance with and without the memory learning's "help." In this test, the feedback knowledge memory model was built using 1000 query sessions report the experimental results. Clearly, the two RF methods achieved the better retrieval performances with the help of memory learning.

This measure shows how often the valid propagations are correct. The so-called valid propagation means its propagation probability is over a confidence threshold. A propagation probability less than threshold implies this propagation happens on a low confidence level. Moreover, in the practical query process, images with a low value to one keyword are hardly retrieved by the system when the user submits that keyword for query. Therefore, only valid propagations are used to finally calculate the accuracy. In the experiment, threshold is 0.2, and the ground truth keyword of an image is its corresponding category name. The accuracy of Bayesian model is the average accuracy of 100 queries. The proposed framework is able to provide more trustworthy annotation propagations.

VI. APPLICATIONS

- Remote and easy learning.
- Useful for areas, where communication skill is a major problem.
- Research work.
- Can be easily modified to recognize different objects like reptiles, leaves etc.
- Can be referred by people in different biological courses to get info within no time.

VII. CONCLUSION

In order to supply effective image retrieval to users, this paper has presented a new memory learning framework in which low-level feature-based RF and semantics-based memory learning are combined to help each other to achieve better retrieval performance.

It creates a feedback knowledge memory model to accumulate user's preferences. More importantly, a learning strategy is introduced to infer the hidden semantics according to the gathered semantic information. In addition, a semantics-based image annotation propagation scheme is described.

The proposed framework is easy to implement and can be efficiently incorporated into an image retrieval system. Experimental evaluations on a large-scale image database have already shown very promising results. However, a limitation of the proposed work is that it somewhat lacks sufficient theoretical justification.

Paper demonstrates the development of Methodology to process the given Image and knowledge base classifier. Classification accuracies are of 85% obtained for all the object types using feature sets i.e., Global and Local features, this is considered satisfactory.

Success of a technology is often due to the confluence of available technology at the time of critical need. Content-Based Image Retrieval of medical images has achieved a degree of maturity at a research level at a time of significant need. In this article we have tried to explore the field through the concept of gaps or shortcomings in comparison with an idealized system. In addressing or minimizing these gaps, a system may be better positioned for use in medical settings described above.

To make CBIR systems more compatible with the requirements of mainstream medical applications, developers should consider: the use of large reference (or gold-standard) data sets and development of reusable code libraries, toolkits or toolboxes, incorporating a large feature set and indexed (rapid) feature retrieval, early adoption of system usability features, and, above all greater collaboration with the medical community.

VIII. FUTURE ENHANCEMENTS

- Computation time taken for data base training is quite more (local and global feature extraction).
- The proposed framework is easy to implement and can be efficiently incorporated into an image retrieval system.
- Experimental evaluations on a large-scale image database have already shown very promising results.
- Our future work will investigate the possibility to develop more sophisticated and theoretical learning schemes.

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