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Research Article

ENHANCED AMBIGUITY RESOLVING PROBLEM IN RANKING BASED CBIR SYSTEM

G.Ponmalar[#1], Joshila Grace L.K[#2]
P.G Student, Dept of CSE, Sathyabama University, Chennai, India.
Asst. Prof, Faculty of Computing, Dept of CSE, Sathyabama University, Chennai, India.
Ponmalar_be_cse@yahoo.co.in

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Abstract:

Problem solving skills have been widely applied in the field of Information Retrieval. The lexicalized concept is an area in IR systems, not concentrated to the core which caters to the issue of ambiguity. The existing approaches such as manifold ranking, k- nearest neighbor ranking etc, were belongs to the Graph Based Ranking Models (GRM) that does not investigated on the issue of ambiguity. Thus, it limited its scope of not applying to large scale systems. This paper focused on solving the issue of ambiguity in Content Based Image Retrieval (CBIR) systems. We describe a theoretical framework that display and predict the subjection between the content and its ambiguity. Then, an enhanced ambiguity resolving technique will be proposed, an insight of building effective content and its ambiguity and reliable ranking. Experimental design and development will be a foundation to creatively solve the ambiguity which effectively works on the large scale systems.

Keywords: Problem Solving Skills (PSS), Information Retrieval (IR), Content Based Image Retrieval (CBIR), Lexicalized concept and ambiguity.

1. Introduction:

In World Wide Web, the important pages are to be visited in a speedier manner. To achieve this, Graph based ranking algorithms are widely used to visit the necessitate pages. These algorithms widely used the existence of explicit links such as hyperlinks, citations between the graph vertices. In even volume of text collections, neither links nor citations exist, the edges between text keywords or a sentence arises[1]. The contextual information of terms and create semantic graphs from text based is also a feasible solution on discovering content similarity. The analysis of text is done in conceptual way that leads to a strong ability to discover the latent similarities between the text segments with different terminology under same subject. This leads to the problem of ambiguity. Problem Solving Skills (PSS) is the technique that applied in the process of Information Retrieval (IR) [2]. The issue of ambiguity will be solved among the text categorization and text summarization. The conventional image retrieval systems used keyword search to extract the information. When the user entered the keyword in Google or yahoo, the user query is matched with the context about the image such as title, manual annotation, web documents etc. This situation leads to the issue of ambiguity. Content Based Image Retrieval systems are used as a solution to recover from these problems. This system was in the field of study for past two decades[3]. The CBIR differs from the conventional systems in terms of low-level features such as global and local features that extracts from the images. Several algorithms were proposed[4,5] which don't overcome the early stage prediction of solving the ambiguity issues. The interactive CBIR system utilizes the tool known as 'Relevance Feedback.

The famous graph based ranking model is the Manifold Ranking (MR) [6, 7.] The MR works on the basis of ranking the data samples on the advent of its implicit geometrical structure on large volumes of data. This systems were widely applied in many applications such as text[7,] image[8, 9] and video[10]. A relative ranking score was assigned for every data sample in MR systems. He et al. [8] firstly applied MR to CBIR, and significantly improved image retrieval performance compared with state-of-the-art algorithms. Though, this system is efficient to predict the image based on the user query, it lacks to deal with the large scale databases due to its computational costs. It leads to heavy computational costs in graph construction and ranking computation stages. In this paper, we tried to focus on solving the ambiguity problem in two approaches. An enhanced ambiguity resolving framework is developed. It works in two stages namely, building efficient image annotation and online models for handling new query and solving the ambiguity. This paper is structured as: Section 1 depicts the Definitions of the CBIR systems and its importance in real world problems. Section 2 portrays the various studies conducted by the researchers in CBIR systems. Section 3 proposes an innovative solution to the problem formulated from the previous studies. An innovative solution has been implemented and their outcomes were depicted in Section 4. Finally, it is concluded in Section 5.

2. Literature Survey:

The issue of ranking, as of late, has increased considerations in both data recovery and machine learning systems. The traditional ranking models can be content based models, like the Vector Space Model, BM25, and the language modeling[11] or connection oriented based models, similar to the renowned PageRank[12] and HITS[13] or cross media models[14]. Another imperative class is to figure out how to rank model, which means to enhance a positioning capacity that joins significance elements and abstains from tuning an expansive number of parameters exactly [15, 16].

Then again, numerous customary models disregard the critical issue of effectiveness, which is vital for ongoing frameworks, for example, a web application. In [17], the researchers introduced a single framework for improving adequacy and effectiveness.

Agarwal [21] proposed to display the information by a weighted graph, and fused this structure into the positioning capacity as a regularizer. Guan et al. [19] proposed a graph based ranking estimation for interrelated multi-type assets to create customized label suggestion. Liu et al. [18] proposed a naturally label positioning scheme by performing an arbitrary stroll over a label comparability diagram. In [20], the researchers made the music suggestion by positioning on a brought together hyper graph, consolidating with rich social data and music content. Hyper graph is another graph based model and has been contemplated in numerous works [21]. As of late, there have been a few papers on accelerating complex positioning. In [22], the researchers parceled the information into a few sections and processed the positioning capacity by a block wise approach.

3. Enhanced Ambiguity Resolving Framework

The proposed works in two phases namely training and testing phase. In training phase, the input image is taken as user query. For that input image, the ambiguity is set. Then the image is annotated and trained. In testing phase, when the user submits the query, the query will be treated into context and content based systems. The ambiguity will be analyzed. Let us consider that the set of data $X = \{x_1, x_2 .... x_n\} \subset \mathrm{R}^m$. With these set of coordinate, it build the graph using traditional models. $W \in R^{n*n}$ represents the adjacency matrix of an item w_{ij} whose weights estimates the edges between point i and j. The weight can be calculated as:

$$w_{ij} = \exp[-d^2(x_i, x_j) / 2\sigma^2)]$$

The distance metric of x_i and x_j is given as the function of d (x_i, xj). The ranking matrix can be assigned to each point x_i and its ranking score as r_i. Then the initial vector assigned as

$$y= [y1 \ldots y_n]^T$$

Here, y_i =1 if x_i is a query otherwise y_i=0.

We addressed the shortcomings of existing methods in two approaches namely efficient graph construction and ranking computation in ambiguity structure.

The objective of our approach is to annotate the image with some intrinsic geometrical properties for learning a latent space. It jointly explores the context and content information based on a latent structure in the semantic concept space.

1) Efficient graph construction:

The graph is built efficiently to handle the large databases. The f(x) for each data point of the labeled as:

$$\hat{f}(x_i) = \sum_{k=1}^{d} z_{ki} f(u_k)$$

Where i=1…n. The constraints should be satisfied are $\sum_{k=1}^{d} z_{ki} = 1$ and $Z_{ki} \geq 0$

2) Ranking Computation:

Ranking computation is estimated from matrix inversion. The data size n cannot be large. Consider the form W= $Z^T Z$. It can rewrite for manifold ranking as:

$$r^* = (I_n - \alpha H^T H)^{-1} y = (I_n - H^T((HH^T - \frac{1}{\alpha} I_d)^{-1} H)y$$

If d<< n, this can speed the task of manifold ranking.

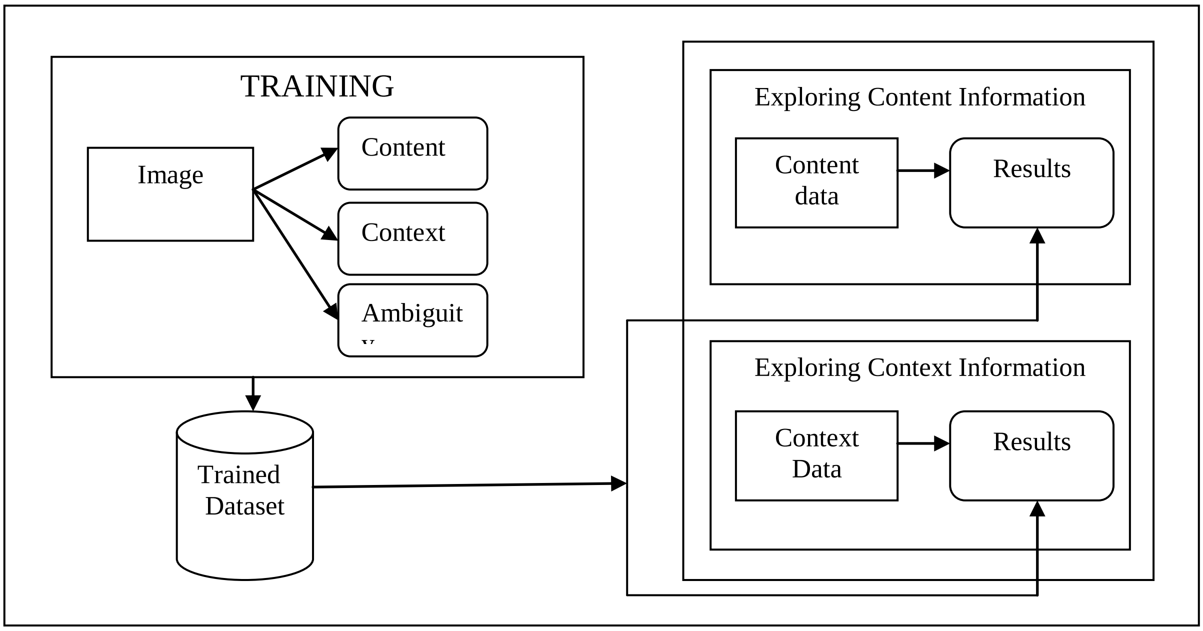

Figure 1. Proposed Architecture.

The Figure 1 depicts the proposed architecture. It has 2 phases, namely training and testing.in training phase the user given input taken as an input image, and that input set as a ambiguity, and trained the dataset and store it in db. The testing phase is used to find the user query that is matched with the dataset. If the user given a matched trained dataset using content and context, the search result will be successful.(the ambiguity will be analysed).

4. Experimental Designs

The images were collected from the COREL dataset which contain 5,000 images. This dataset is widely used for CBIR systems [2]. This contains 50 different categories with 100 images per category. This image is used as a query for testing. The experimental designs were presented as follows:

The below Figure 2 describes, once the user submit the query input image is defined based on the image position. The image position is set by x and y axis, once the input given it set the position based on the image, and then store it in a db. While the user submit the query to search the content it will check the db their respective position stored by db, based on the position it define the image which the user given.

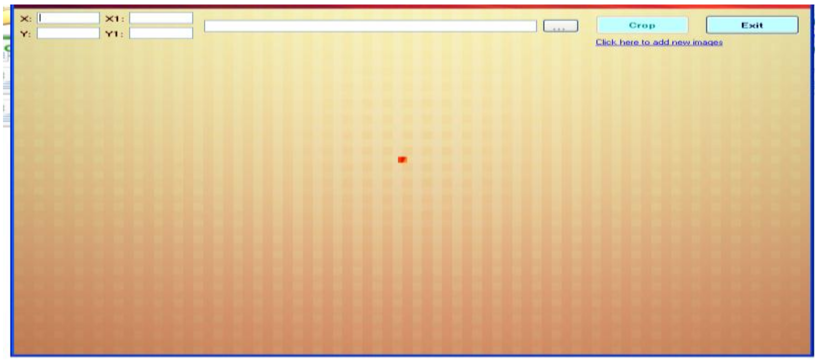

Figure 2. Defining the intrinsic geometric properties of an image.

The Figure 3 depicts after defining the image based on geometric position, insert the image, image type then click add button. Once you added the image to dataset, then create the ambiguity id, name and select the image type which you given in the insertion to the particular image.

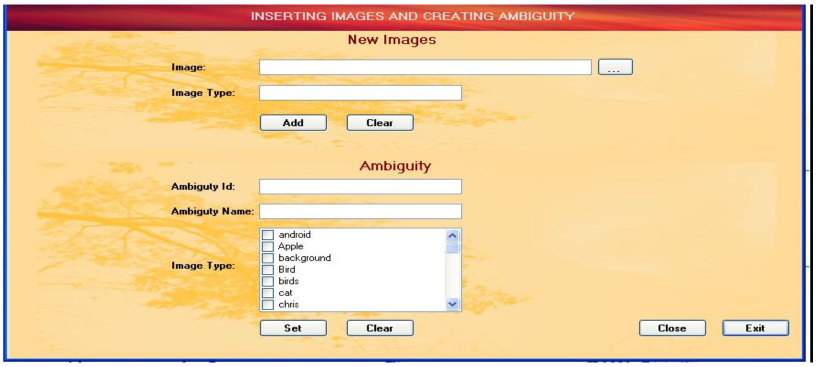

Figure 3. Inserting the images and creating the ambiguity

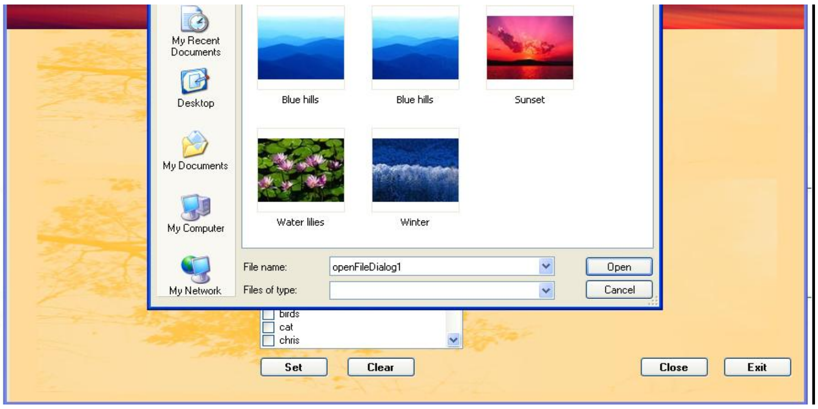

Figure 4. Inserting the image as the query.

The below Figure 4 describe after successful insertion image and creating ambiguity, the new image is set as a input query in the trained dataset.like more no.of images stored in the trained dataset.

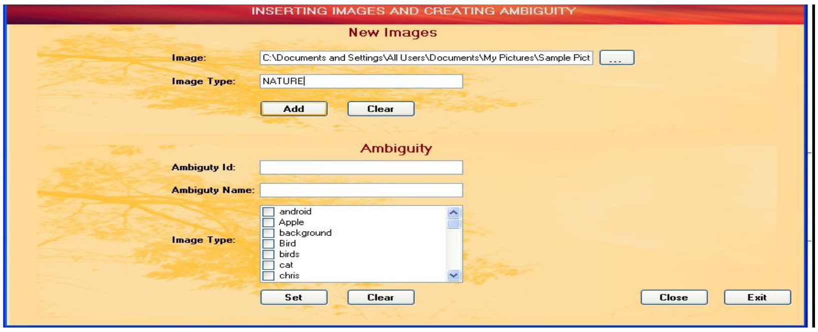

Figure 5. Setting the ambiguity for image.

The above Figure 5 describe after setting the image as query by the user, the ambiguity is set for all the images which we are stored in dataset. once the image is selected by user, image will set the ambiguity for the particular images.

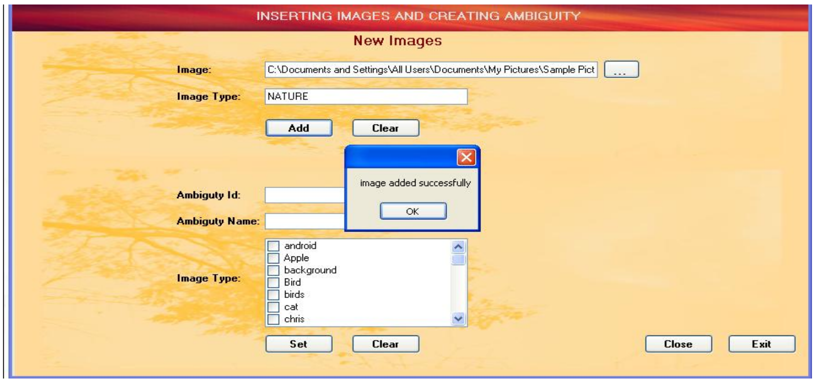

Figure 6. Successful insertion of the image.

The above Figure 6 depicts once image is added successfully, particular image will be set the ambiguity based on image typ. User can search the image, using EMR to resolve the repeated content, and reduce the compile time efficiently.

5. Conclusion

Content Based Image Retrieval (CBIR) is the most effective and important retrieval method. This paper concentrated on providing solution to the ambiguity problem. An enhanced ambiguity resolving framework is designed with the advent of manifold ranking. We extend this scheme to handle the large scale databases. Our experimental design proves that this enhanced ambiguity resolving framework fastened the image search in a less computational time.

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