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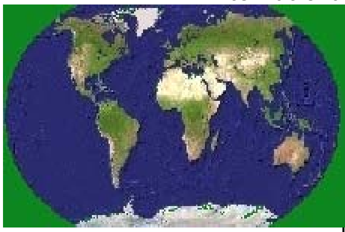

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Re-ranking of images based on textual and visual context

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Abstract
In this paper, we propose re-ranking of images which will be based on textual and visual context. In early days various web-search engines are available to adopt Image re-ranking as an effective way to improve the results of web-based image search. Two types of image search methods are available in the Internet. They are query keyword based model and content based image retrieval models. Text query are used in the textual image retrieval model. Visual re-ranking has been widely deployed to refine the quality of conventional content-based image retrieval engines.
The query keyword is given as input query, a pool of images are first retrieved based on textual information. It becomes difficult for user to interpret intention only on query keywords which leads to ambiguous and noisy results which are far different from user's satisfaction. It helps user to ask to select a query image from image pool with minimum effort and images from image pool retrieved by text-based search are re-ranked based on both visual and textual content.
Firstly Adaptive Weight Schema is used for the similarity analysis and categorizing the images and re-ranking it with adaptive weighting schema. Feature weight learning algorithm is applied to estimate feature weights for the images and its category. Secondly query is expanded with keyword and visual information by using the visual content of the query image selected by the user and by using image clustering then, query keywords are expanded and image pool is enlarge that contain relevant images and finally these are expanded by using keyword expansion. All these are done very easily and automatically without any extra work.

Keywords: Image search, intention, image re-ranking, adaptive similarity, keyword expansion

1. Introduction

With the Internet explosion, tremendous amounts of multimedia information, such as images, videos, and ashes, become available on the Web. There are many search engine are available in the market such as Google, Bing, Microsoft etc. Today's commercial Internet scale image search engines use only text information. An internet image search engine is an essential aspect for web searchers to find desired images. With the emergence of the Internet, billions of images are now widely available. Image searching is the process of finding relevant images on web search engines. A huge database has been maintained to store and retrieve images at server side. The image ranking as an effective way to improve the results of Web based image search has been adopted by current commercial search engines. The approaches of retrieving and ranking images from large-scale datasets can be largely divided into the following two categories:

1.1 Text-based approaches: the search engine returns corresponding images by processing the associated textual information, such as file name, surrounding text, URL, etc., according to keywords input by users. Text-based search techniques have been verified to perform well in textual documents; they often result in mismatch when applied to the image search. The search results are noisy and consist of images with quite dissimilar semantic meanings.
For example a search by the keyword "Bat" as query. They associated with several categories, such as "Cricket bat", "Hockey bat" and "bat" due to the ambiguity of the word "Cricket bat". The ambiguity problem appears for several reasons first, the query keywords' context may be richer than users' assumption.

Figure 1."Bat" as query result before re-ranking**.**

Figure 2. Result after re-ranking.

1.2 Content-based approaches: Another technique CBIR (Content based retrieval) with relevance feedback. Users label multiple positive and negative image examples. This type of engine extracts semantic information from image content features, such as color, shape, texture, spatial location of objects in images etc. Retrieve object from the images. We believe that adding visual information is helpful to capture user intention and retrieves quality images. Some steps required for this paper.

1.2.1 Adaptive Similarity:
Adaptive similarity is used for categorizing the images and re-ranking it with adaptive weighting schema. This correspondence between the query image and its proper similarity measurement reflects the user intention. Users can easily categories images into different classes such as people, natural scene, logo, fruit or animal then observed that images inside these categories usually agree on the relative importance of features for similarity calculations.

1.2.2 Keyword Expansion:
The keywords provided by users tend to be short. They cannot describe the content of images accurately. The query keywords' meanings may be richer than users' expectations. For example, the meanings of the word "Bat" include Cricket bat, Hockey bat, and Bat. If user can enter incorrect query or some missing words in query because of lack of user knowledge, then Keyword expansion can be used for proper search query (e.g. "laptops" related searches are Dell, Lenovo, and hp).

1.2.3 Visual Query Expansion:
The goal of visual query expansion is to obtain multiple images by using visual similarity metric. To capture the user's intention only one query image is not enough. These similarity metrics reflect users' intention which gives better images.

1.2.4 Image Pool Expansion:
Image pool expansion shows the top ranked images from the image pool and user may select choice of his image from that image pool. The image pool is enlarged through combining the original image pool retrieved by the query keyword and an additional image pool retrieved by the expanded keywords. Images in the enlarged pool are re-ranked using the learned query specific visual and textual similarity metrics.

1.2.5 Re-Ranking Result:
The image cluster size is selected as visual query expansion and its similarity to the query image indicate the confidence that the expansion captures the user's search intent.

2 Working Model
The flow chart of our system is shown in Figure 3. A novel Internet based image search approach. It requires the user to click on one query image and images can be retrieved from pool by using text-based search are re-ranked based on both visual and textual content. To capture the users intention images from one-click query image in following steps:

Input
Step 1) text-based query:
Firstly the user has to submit the query keyword Q. A pool of images is retrieved by text-based search (Fig. 3). Then the user is asked to select a query image from the image pool.

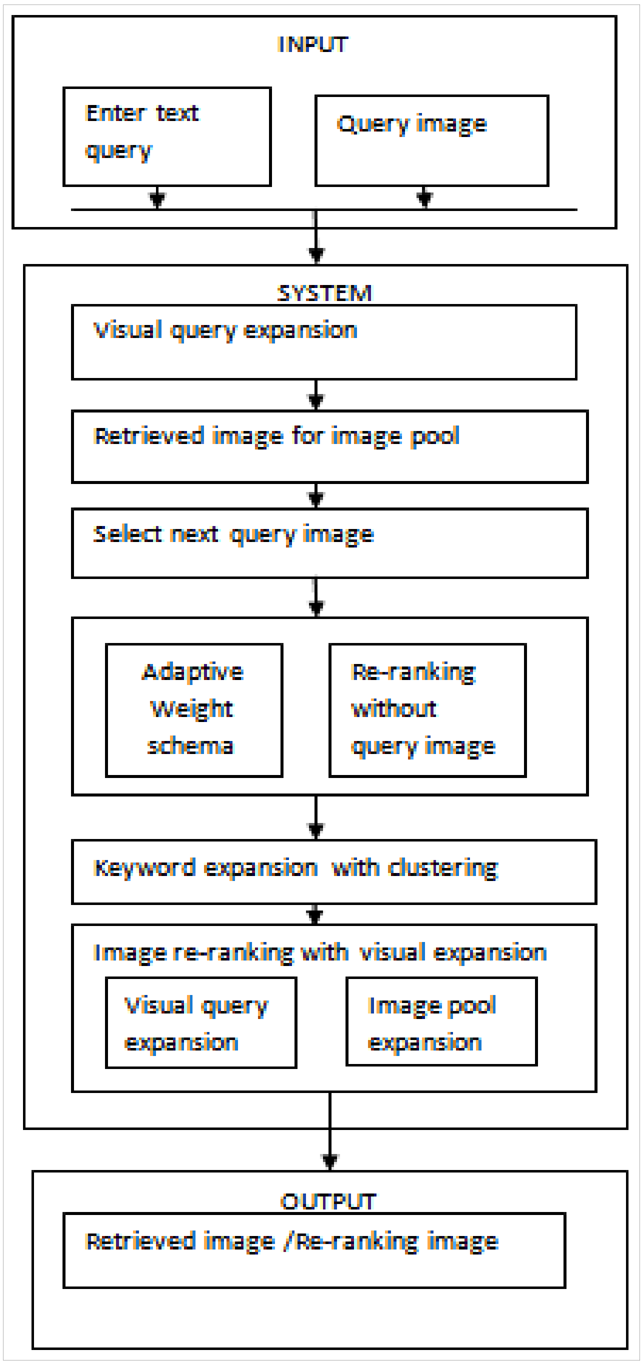

Figure 3: Architecture of the proposed system.

System

Step 2) Adaptive weighting schema:

The query image is classified as the predefined adaptive weight categories. Human can be classifying the images such as scene, object, portrait, or people. And then observed that images inside these categories usually agree on the relative importance of features for similarity calculations. Related images having same weight make groups of those images in one category.

The query images into several typical categories adjust feature weights within each category. Adaptive weighting schema as shown in Fig.3

Step 3) Re-ranking without query expansion:

The query image is classified by the predefined adaptive weight categories. Images in the pool are re-ranked (Fig. 3) based on their visual similarities to the query image and the similarities are computed using the weight schema specified by the category to combine visual features.

Step 4) Keyword Expansion:

In the keyword expansion step (Fig. 3), words are extracted from the textual contents (such as image file names and surrounding texts in the html pages) of the top k images most similar to the query image. The tf-idf method is used to rank these words. Only the top m words are reserved and processed for further processing. Because the initial image re-ranking result is noisy, the top k images may have a large diversity of semantic meanings and cannot be used as visual query expansion. The word with the highest tf-idf score computed from the top k images is not reliable to be chosen as keyword expansion either. In this system, reliable keyword expansions are found through further image clustering. For each candidate word w0, we find all the images containing w0and group them into different clusters fci;1; ci;2; . . . ; ci;tig based on visual content. As shown in Fig. 3, images with the same candidate word may have a large diversity in visual content. Images assigned to the similar cluster have higher semantic consistency since they have high visual similarity to one another and contain the same candidate word.

Step 5) Visual Query Expansion:

The clusters contain of various candidate words, cluster ci, j with the largest visual similarity to the query image is selected as visual query expansion and its corresponding word w0 is selected to form keyword expansion.

Q’=Q+w0

A query image having visual as well as textual similarity metric and that are learned from both the query image and the visual query expansion

Step 6) Image Pool Expansion:

The image pool is enlarged through combining the original image pool retrieved by the query keywords Q provided by the user and an additional image pool retrieved by the expanded keywords Q’ (Fig. 3).

Output

Step 7) Re-Ranking images or retrieved images:

Images are present in the enlarged pool. These images are re-ranked using the learned query-specific visual and textual similarity metrics (Fig. 3). The size of the image cluster selected as visual query expansion and its similarity to the query image indicate the confidence that the expansion captures the user’s search intention from the pool. If they are below certain thresholds, expansion is not used in image re-ranking.

3 Algorithms:

3.1 Algorithm for Weight algorithm:

1. Input: Initial weight Wi for all query image I in the current intention category C.
   Similarity matrix Mf[i] for all query image i & features f.
2. Initially set step p=1, set initial weight Wi′=Wi for all images of i.
   While not converged do
   For each query image i ∈C do

3. Select best feature f & corresponding similarity matrix Mf[i] for current
   Re-ranking problem under weight Wi^P. then
   Calculate enable wt is βp.
4. Adjust weight Wi^p+1(j,k) α Wi^p(j,k). exp{βp[Mf[i,j]-βp[Mf[i,k]};
5. Wi^p+1 make to be distributed.
6. p++;
   End for
   End while.
7. Final output: final optimal similarity measure for current intension category.
   Matrix Mf^q[i , j]=∑βp Mf[i , j]/ $\sum \beta p$

3.2 Algorithm for picture analysis or get frequently used colors:

1. Input: Input image I1
2. Initialized: Create empty dictionary dctColorIncidence <int, int> ();
3. for each pixel Pi of I1 do
4. Get pixel value.
5. if(dctColorIncidence.Keys contains(pixelValue)) then
   Increment index of that pixel value in dictionary
6. else
   Assign 1 to at index pointed by pixel value in dictionary.
7. end for
8. Sort dictionary
9. Output: Return first element of dictionary as mostUsedcolor.

3.3 Algorithm for Face Detection:

1. Input: Input image I1
2. Initialized: opencv library. Set no of face nf=0;
3. Create HaarCascade classifier object face-cascade. Load train xml file into object.
4. Create HaarCascade classifier object eye-cascade. Load train xml file into object.
5. Get input image I1.
6. Convert it into Gray scale Gi.
7. Detect HaarCascade of Gi.
8. Detect faces and increment nf.
9. Output: Return detected faces nf.

Conclusion:

In this paper, we propose a re-ranking of imageswhich is done by one-click of user and improve quality of images by acquiring user intention. The weight schema is proposed to combine visual features and to compute visual similarity adaptive to query images. It improves image search with faster speed and high quality on web. With this project we conclude that it improves user experience and also user gets the exact search as the user wants. We also build a large labeled database from Internet to share to the community. Using the developed technology, we implemented a real-time online image search engine, combining text and Intent Search.

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