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Extended Image Features for User Intention Refined Image Search

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***Abstract:** Web image search is the major aspect in present days like Google image search. It is difficult for them to interpret users' search intention only by query keywords and this leads to ambiguous and noisy search results which are far from satisfactory. For producing these results efficiently traditionally used a novel Internet image search approach[1], this technique only requires the user to click on one query image with the minimum effort and images from a pool retrieved by text-based search are re-ranked[2] based on both visual and textual content. Based on the keyword expansion and user intention we have to retrieve relevant results efficiently. Image retrieval using only color features often gives disappointing results, because in many cases, images with similar colors do not have similar content. Content Based Image Retrieval (CBIR) is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. We provide a comparison between retrieval results based on features extracted from the whole image, and features extracted from image regions. The results demonstrate that a combination of global and region based approaches gives better retrieval results for almost all semantic classes.*

***Index Terms:** Image re-ranking, Adaptive similarity, Keyword expansion, Content based image retrieval, Region based features, Global based features, Texture, Color, Gabor filter.*

I. INTRODUCTION

Image classification is important to tackle a variety of real-world problems such as computer aided diagnosis and image surveillance, and much research effort has been made in the computer vision community. A feature extraction is especially a fundamental procedure to improve the performances of the image classification. The search engine returns thousands of images ranked by the keywords extracted from the surrounding text. It is well known that text-based image search [3] suffers from the ambiguity of query keywords.

Figure 1: Top ranked images returned from Bing image [4] search using "apple" as query.

The ambiguity issue occurs for several reasons. First, the query keywords' meanings may be richer than users' expectations. In order to solve the ambiguity, additional information has to be used to capture users' search intention. One way is text-based keyword expansion, making the textual description of the query more detailed.

Content Based Image Retrieval (CBIR) [5] is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. A region-based retrieval system applies image segmentation to decompose an image into regions, which correspond to objects. The object-level representation is intended to be close to the perception of the human visual system (HVS). Since the retrieval system identifies what objects are in the image, it is easier for the system to recognize similar objects at different locations and with different orientations and sizes. Traditionally intent based image search follows adaptive similarity it is motivated for intent that a user always has specific intention when submitting a query image. Keyword expansion is another process for retrieving relevant results. In this technique query keywords input by users tend to be short and some important keywords may be missed because of users' lack of knowledge on the textual description of target images. The image pool retrieved by text-based search accommodates images with a large variety of semantic meanings and the number of images related to the query image is small.

And last one is Visual query expansion, in that one query image is not diverse enough to capture the user's intention. By extending the features of the image efficiently relative accuracy for image search will be gained. In this image search we consider the following features

Higher-order Co-occurrence Features:

The co-cluster assignment functions *gk* discriminatively characterize joint (pair-wise) quantitative data, and then we obtain the co-occurrence features of usually lower dimensionality D than C^2 of the standard features using the factorized functions $f_i\, f_j$. This is because the function *gk* can naturally cope with the joint relationship of correlated data at once without assuming factorization $f_i\ f_j$. Based on such fact, we further develop the higher-order co occurrence features on the multiples more than doubles (pairs). In this paper, we consider the co-occurrence of *quadruplets* which are pairs of pair-wise data.

Moment invariants:

Moment invariants [7] were first introduced by the Hu. By image functions we understand any real function f(x, y) $\in Li$ having a bounded support and a non-zero integral. Translation and scale variance of a dimension moment invariants are easy to be eliminated.

Image matching and retrieval:

The similarity between a query image, *Q*, and a database image, *B*, is defined in term of the distance, *DG*(*Q*, *B*), between them, which is assessed according to the extracted texture and color features. Two images are equivalent when the distance value between them is zero, and the similarity between them decreases as the distance increases. Consider the above features efficiently we solve the experimental research on each feature in extracting images from various data base applications.

II. BACKGROUND WORK

Many Internet scale image search methods are text-based and are limited by the fact that query keywords cannot describe image content accurately. Content-based image retrieval [6] uses visual features to evaluate image similarity. In order to reduce users' burden, pseudo relevance feedback expanded the query image by taking the top *N* images visually most similar to the query image as positive examples. However, due to the well known semantic gap, the top *N* images may not be all semantically-consistent with the query image. Using Visual expansion features of the image process.

They needed a pre-defined concept lexicons whose detectors were off-line learned from fixed training sets. These approach were suitable for closed databases but not for web-based image search, since the limited number of concepts cannot cover the numerous images on the Internet.

Keyword expansion is used to expand the retrieved image pool and to expand positive examples. Keyword expansion was mainly used in document retrieval. Some algorithms generated tag suggestions or annotations based on visual content for input images. Their goal is not to improve the performance of image reranking. Although they can be viewed as options of keyword expansions, some difficulties prevent them from being directly applied to our problem. Most of them assumed fixed keyword sets, which are hard to obtain for image re-ranking in the open and dynamic web environment.

III. EXISTING SYSTEM

Current internet driven image search engines use only keywords as queries. Users type query keywords in the hope of finding a certain type of images. The search engine returns thousands of images ranked by the keywords extracted from the surrounding text. Text-based image searching suffers from the ambiguity of query keywords. Uses Adaptive Weight Schema to capture user Intent and re rank results based on it.

Pre Operations:

Adaptive Weight Schema comes under pre-operations that has two sub categories

Query Categorization:

The query categories we considered are: General Object, Object with Simple Background, Scenery Images, Portrait, and People.

Feature Fusion:

For each query category, pre-training is required.

Dynamic Operations:

Keyword Expansion is performed which is a dynamic operation because it has to be performed while retrieving results for a search. Once the top k images most similar to the query image are found according to the visual similarity metric, words from their textual descriptions are extracted and ranked, using the term frequency-inverse document frequency (tf-idf) method. The top m (m = 5 in our experiments) words are reserved as candidates for Visual query expansion.

Visual Query Expansion is also a dynamic operation to continuously alter the results based on user intent validations.

Image Pool Expansion is also a dynamic operation to continuously execute the queries of Visual Query Expansion and obtain results.

Based on these Pre and dynamic operations will have customized results of their choice based on their intent.

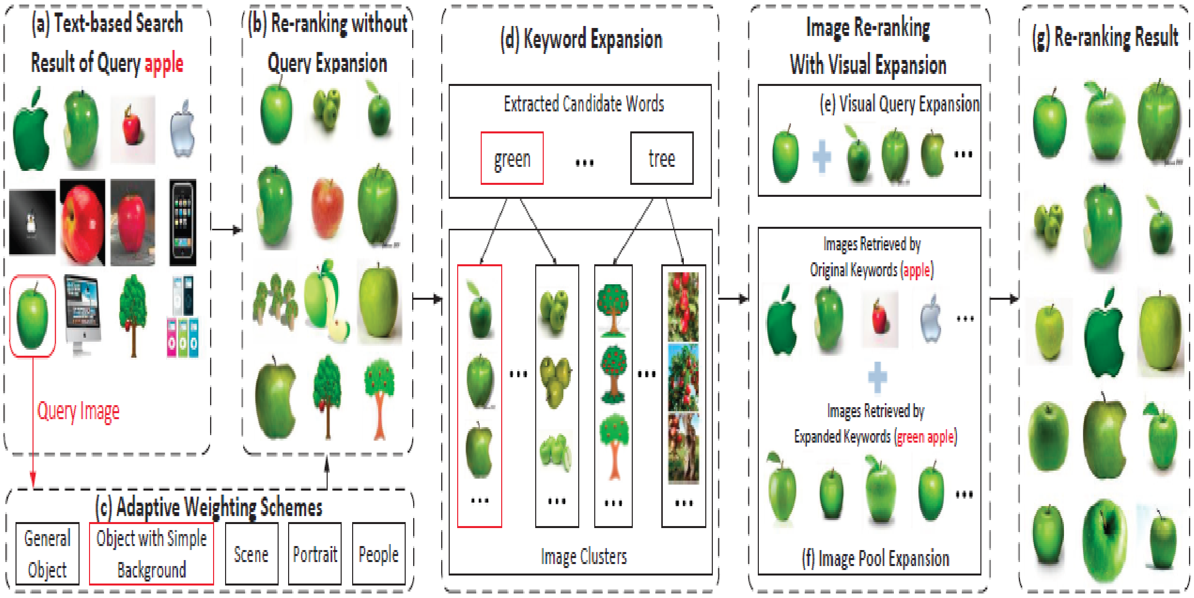
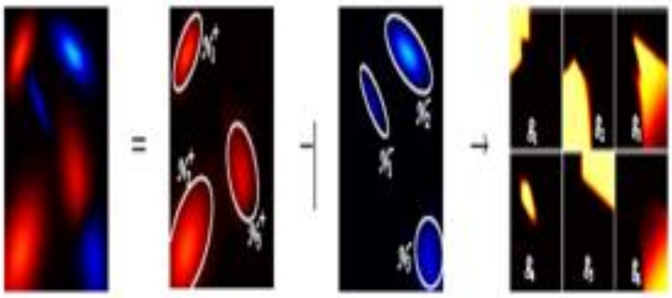


Figure 2: Image retrieval approaches based on process generation with suitable examples.

The features we used for query categorization are: existence of faces, the number of faces in the image, the percentage of the image frame taken up by the face region, the coordinate of the face center relative to the center of the image directionality. The user intention is first roughly captured by classifying the query image into one of the coarse semantic categories and choosing a proper weight schema accordingly. Intention specific weight schema is proposed to combine visual features and to compute visual similarity adaptive to query images. Without additional human feedback, textual and visual expansions are integrated to capture user intention. Expanded keywords are used to extend positive example images and also enlarge the image pool to include more relevant images.

IV. PROPOSED SYSTEM

The proposed method constructs the *co-clusters* to discriminatively quantize joint primitive quantitative data, such as pair-wise pixel intensities, unlike the standard co-occurrence methods that utilize simple clusters trained in an unsupervised manner for quantizing point-wise data. The discriminative co-clusters effectively exploit the co-occurrence characteristics even by a fewer number of cluster components, resulting in low-dimensional co-occurrence features. We propose a method to extract higher-order co-occurrence image features. The proposed method is built upon the *co-clusters* discriminatively quantizing *pair wise* quantitative data, in contrast to the standard methods that utilize simple clusters of point-wise data trained in an unsupervised manner. The discriminative co-clusters directly capture the statistical characteristics, *i.e.*, co-occurrence, of pair-wise data, and effective co-occurrence features are extracted by using even a small number of the co-clusters, which results in low dimensionality.



cw W pw W^+ nw W^- co-clusters g_k

Figure 3: Construction of discriminative co-clusters [12]. Where cw – Classifier Weight

Pw – Positive Weight nw- Negative Weight

Thus, we can develop the higher-order co-occurrence feature of feasible dimensionality based on co-occurrences of quadruplets which are pairs of pair wise data represented by the discriminative co-clusters. The higher-order co-occurrences exploit richer information in image textures by taking into account of higher-order relationships in multiples more than doubles (pairs) and contribute to improve the performance of image classifications.

Higher-order co-occurrence features:

We apply the proposed method to two image classification tasks: cancer detection and pedestrian detection which result in binary (two class) classifications as cancer vs. non-cancer and pedestrian vs. non-pedestrian.

Global Content Based Image Retrieval System:

In the GCBIR [8] system, we used global color histograms to extract the color features of images. We adopt to use the HSV (Hue, Saturation, and Value) color space for its simple transformation from the RGB (Red, Green, and Blue) color space, in which images are commonly represented. The HSV color space is quantized into 108 bins by using uniform quantization (12 for H, 3 for S, and 3 for V); the choice of these parameters was motivated by [17]. Since Hue (H) has more importance in human visual system than saturation (S) and value (V), it is reasonable to assign bins in the histogram to Hue more than the other components. It is straightforward to generate the histograms of color images using the selected quantized color space.

They needed a pre-defined concept lexicons whose detectors were off-line learned from fixed training sets. These approaches were suitable for closed databases but not for web-based image search [9], since the limited number of concepts cannot cover the numerous images on the Internet.

Step1: Convert the RGB image into gray level image.
Step2: Construct a bank of 24 Gabor filters using the mother Gabor function with 4 scales and 6 orientations.
Step3: Apply Gabor filters on the gray level of the image.
Step4: Get the energy distribution of each of the 24 filters responses.
Step5: Compute the mean, μ, and the standard deviation, σ, of each energy distribution.
Step6: Return the texture vector, *TG*, consisting of 48 attributes calculated at step 5. The attributes of the texture features vector may have different ranges; therefore, Min-Max normalization is used to make all the texture features have the same effect in measuring image similarity.

Figure 4: Image retrieval features for accessing global features.

Color histogram [10] as a global color feature and histogram intersection as color similarity metric combined with Gabor texture have been proved to give approximately as good retrieval results as that of region based retrieval systems. We have increased the effectiveness of the RCBIR system by estimating texture features from an image region after segmentation instead of using the average value of group of pixels or blocks through the segmentation process.

V. EXPERIMENTAL ANALYSIS

In this section consider the features of the traditional and proposed approaches as follows:

Image database and implementation environment:

The data base was used to access the evaluation of the image retrieval process. It consists of 1000 images, a subset of the Corel database, which has been manually selected to be a database of 10 classes of 100 images each. The images are of size 384×256 or 256×384 pixels. This database was extensively used to test many CBIR[11] systems because the size of the database and the availability of class information allows for performance evaluation.

Evaluation:

We randomly selected 20 images as queries from each of the 10 semantic classes in the database. For each query, the precision of the retrieval at each level of the recall is obtained by gradually increasing the number of retrieved images.

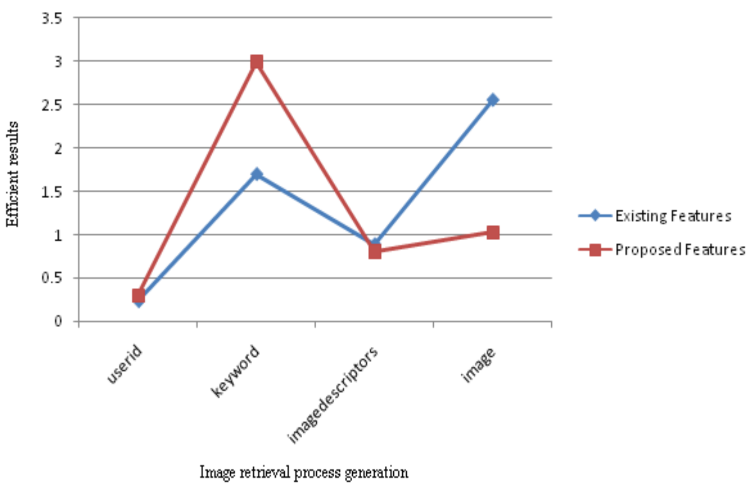


Figure 5: Comparison results with image processing in efficient image retrieval.

In order to evaluate the performance, we used the same approach since we refer to their comparison results. For each category in the 1000 database images, we randomly selected 20 images as queries. For each query, we examined the precision of the retrieval based on the relevance of the semantic meaning between the query and the retrieved images.

VI. CONCLUSION

We used Gabor filter, which is a powerful texture extraction technique, to describe the content of image regions or the global content of an image. Color histogram as a global color feature and histogram intersection as color similarity metric combined with Gabor texture have been proved to give approximately as good retrieval results as that of region based retrieval systems. Based on the keyword expansion and user intension we have to retrieve relevant results efficiently. Image retrieval using only color features often gives disappointing results, because in many cases, images with similar colors do not have similar content. Content Based Image Retrieval (CBIR) is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features. We provide a comparison between retrieval results based on features extracted from the whole image, and features extracted from image regions. The results demonstrate that a combination of global and region based approaches gives better retrieval results for almost all semantic classes.

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