One Click Intent Image Search

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Abstract:

In this paper we are going to enter a keyword for image to search. We will get number of images based on that keyword. Then from certain group number of images .A click or feedback is taken from user as reference image. Then we apply content based image retrival.

Content-based image retrieval (CBIR) is an image search technique where images are selected from an image database by using a reference image rather than metadata, such as keywords, tags and descriptions associated with that image. Here, input for the search is an image, and the output is similar images from the database. The similarity between two images is measured by calculating the distance between the two images. That distance is calculated from feature vectors, and the feature vectors are constructed from the content of the image. Here, content refers to color, texture and shape of the image.

Keywords: Cbir, Simrank, Haar, Haar coeffiecient,Transform, mean, skew

Introduction

Existing Systems:

In Existing system, one way is text-based keyword expansion, making the textual description of the query more detailed. Existing linguistically-related methods find either synonyms or other linguistic-related words from thesaurus, or find words frequently co occurring with the query keywords.

Proposed system:

In Proposed system, we propose a novel Internet image search approach. It requires the user to give only one click on a query image and images from a pool retrieved by text based search are re-ranked based on their visual and textual similarities to the query image. We believe that users will tolerate one-click interaction which has been used by many popular text-based search engines. For example, Google requires a user to select a suggested textual query expansion by one-click to get additional results. The key problem to be solved in this paper is how to capture user intention from this one-click query image.

To implement this we are going to use two algorithm

1.Simrank Algorithmn

2.Haar Wavelet

1] SimRank Algorithm

Many application require a measure of "similarity" between objects. One obvious example is the "find-similar-document" query, on traditional text corpora or the World Wide Web. More generally, a similarity measure can be used to cluster objects, such as for collaborative filtering in a recommender system which ―similar‖ users and items are grouped based on the users' preferences.

Various aspects of objects can be used to determine similarity, usually depending on the domain and the appropriate definition of similarity for that domain. In a document corpus, matching text may be used, and for collaborative filtering, similar users may be identified by common preferences. SimRank is a general approach that exploits the object-to-object relationships found in many domains of interest.

The intuition behind the SimRank algorithm is that, in many domains, similar objects are referenced by similar objects. More precisely, objects and are considered to be similar if they are pointed from objects and respectively, and are themselves similar. The base case is that objects are maximally similar to themselves.

It is important to note that SimRank is a general algorithm that determines only the similarity of structural context. SimRank applies to any domain where there are enough relevant relationships between objects to base at least some notion of similarity on relationships. Obviously ,similarity of other domain-specific aspects are important as well; these can — and should be combined with relational structural-context similarity for an overall similarity measure. For example, for Web pages SimRank can be combined with traditional textual similarity; the same idea applies to scientific papers or other document corpora. For recommendation systems, there may be built-in known similarities between items (e.g., both computers, both clothing, etc.), as well as similarities between users (e.g., same gender, same spending level). Again, these similarities can be combined with the similarity scores that are computed based on preference patterns, in order to produce an overall similarity measure.

2] Haar Wavelet

This sequence was proposed in 1909 by Alfréd Haar. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. The study of Wavelets, and even the term "wavelet", did not come until much later . The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions, such as monitoring of tool failure in machines.
The Haar wavelet's mother wavelet function ψ(t) can be described as:

$$\psi(t) = \begin{cases} 1 & ,0 \le t < \frac{1}{2} \\ -1 & ,\frac{1}{2} \le t < 1 \\ 0 & ,\text{otherwise} \end{cases}$$

If a data set $X_0, X_1 \dots X_{N-1}$ contains N elements, there will be N/2 averages and N/2 wavelet coefficient values. The averages are stored in the first half of the N element array, and the coefficients are stored in the second half of the N element array. The averages become the input for the next step in the wavelet calculation. The Haar equations to calculate an average i a and a wavelet coefficient i c from an odd and even element in the dataset are

$$Ai = Xi + Xi + 1\backslash 2$$

$$Ci = Xi - Xi + 1\backslash 2$$

Steps for a 1D Haar transform of an array of N elements are as follows:

1. Find the average of each pair of elements using Equation 1. (N/2 averages)

2. Find the difference between each pair of elements and divide it by 2. (N/2 coefficients)

3. Fill the first half of the array with averages.

4. Fill the second half of the array with coefficients.

5. Repeat the process on an average part of the array until a single average and a single coefficient are calculated.

Steps for a 2D Haar transform are:

1. Compute 1D Haar wavelet decomposition of each row of the original pixel values.

2. Compute 1D Haar wavelet decomposition of each column of the row-transformed pixels.

Red, green and blue values are extracted from the images. Then we apply the 2D Haar transform to each color matrix.

By Haar wavelet we extract all the three features like color ,texture and shape.

Color is one of the most commonly used visual features in content-based image retrieval. Color features have been found to be effective for measuring similarity between images. One of the main aspects of color feature extraction is the choice of a color space. A color space is a multidimensional space in which the different dimensions represent the different components of color. An example of a color space is RGB.

$$E = \sum_{j=1}^{N} \frac{1}{N} pij$$

where:
N = number of pixels in the image
p_{ij}= value of the j-th pixel of the image at the i-th color channel p_{ij}

The second color moment is the standard deviation, which is obtained by taking the square root of the variance of the color distribution.

$$\sigma = \sqrt{\left(\frac{1}{N}\right) \sum_{j=1}^{N} (pij - Ei)^2}$$

Related Work

Content-based image retrieval has become a prominent research topic, and researchers have proposed different methods to improve the system.

Color features are the most widely used visual features in CBIR systems. The color indexing work of Swain and Ballard , which is based on color histograms, has demonstrated the potential of using color for indexing. Stricker and Orengo have shown that moment-based color distribution features can be matched more robustly than color histograms because histograms do not capture spatial relationships of color regions. Hence, in our proposed method, color moments are used for color feature extraction.

Texture is an important feature for CBIR systems. Various techniques have been developed for measuring texture similarity. Tamura et al. took the approach of devising texture features that correspond to human visual perception. They defined six textural features (coarseness, contrast, directionality, line-likeness, regularity and roughness) and compared them with psychological measurements for human subjects. The first three components of Tamura features have been used in some early well-known image retrieval systems, such as QBIC . Wavelet transform provides a multi-resolution approach to texture analysis and classification. Khan et al. used the Haar wavelet transform for texture feature extraction.

Combination of features is also used in content-based image retrieval. Choras et al. proposed an integrated color, texture and shape feature extraction method in which Gabor filtration is used to determine the number of regions of interest (ROIs). They calculated texture and color features from the ROIs based on threshold Gabor features and histograms, color moments in luminance-bandwidth-chrominance space, and shape features based on Zernike moments.

System Architecture

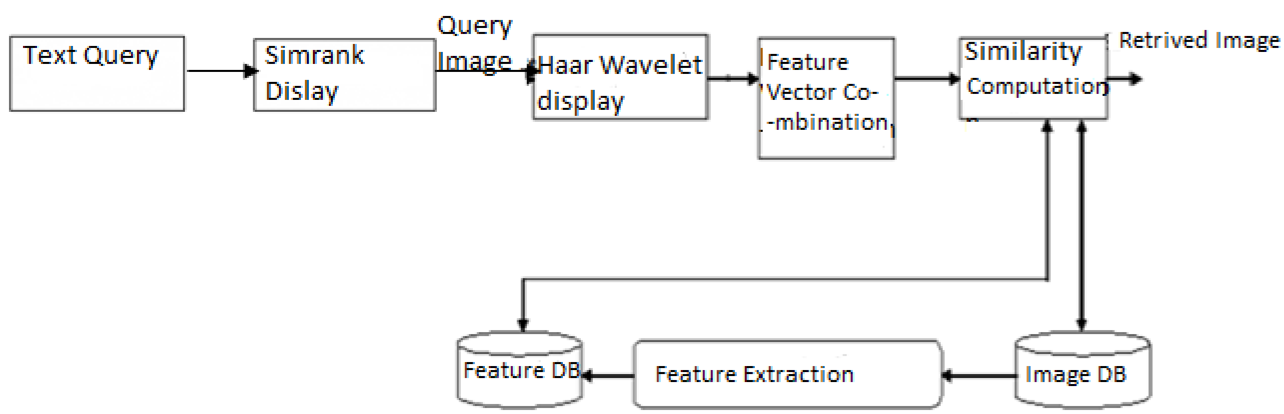

Fig 1. System Architecture

Similarity Measure

The similarity between two images is computed by calculating the distance between feature representation of the query image and feature representation of the image in the dataset. We use Canberra distance for distance calculation of the feature vectors

$$disp(q,d) = \sum_{i=1}^{N} \frac{qi - di}{qi + di}$$

where :
q=(q1,q2,q3………) is the feature vector of the query image,
d=(d1,d2,d3….) is the feature vector of the image in the database,
n = number of elements of the feature vector.
If the distance between feature representation of the query image and feature representation of the database image is small, then it is considered similar.

The final distance between the query image and the image in the database is calculated as follows:

D=d1*w1+d2*w2

where:

d1= calculated distance using Haar wavelet features
w1= weight for Haar wavelet features
d2= calculated distance using color features
w2= weight for color features

Conclusion

In this topic, we propose a novel Internet image search approach which only requires one-click user feedback. 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. This framework makes it possible for industrial scale image search by both text and visual content. One shortcoming of the current system is that sometimes duplicate images show up as similar images to the query. This can be improved by including duplicate detection in the future work. Finally, to further improve the quality of re-ranked images, we intent to combine this work with photo quality assessment work in to re-rank images not only by content similarity but also by the visual quality of the images

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