VISUAL RERANK: APPLYING TO LARGE SCALE IMAGE SEARCH AS A SOFT COMPUTING APPROACH

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Abstract

The explosive growth and widespread accessibility of community-contributed media content on the Internet has led to a surge of research activity in visual search. Also, the fast development of internet applications and increasing popularity of modern digital gadgets leads to a very huge collection of image database. However, it remains uncertain whether such techniques will generalize to a large number of popular Web queries and whether the potential improvement to search quality guarantees additional computational cost. Due to the success of text based search of Web pages and in part, to the difficulty and expense of using image based signals, most search engines return images solely based on the text of the pages from which the images are linked. No image analysis takes place to determine relevance/quality. This can yield results of inconsistent quality.

So, such kind of visual search approach has proven unsatisfying as it often entirely ignores the visual content itself as a ranking signal. To address this issue, visual reranking, defined as reordering of visual images based on their visual appearance can be used. The major advantages of this approach is that, it improves the search performance.

Keywords

Content Based Image Retrieval, Image Ranking, Image Searching, Semantic Matching, Visual Reranking.

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1. Introduction

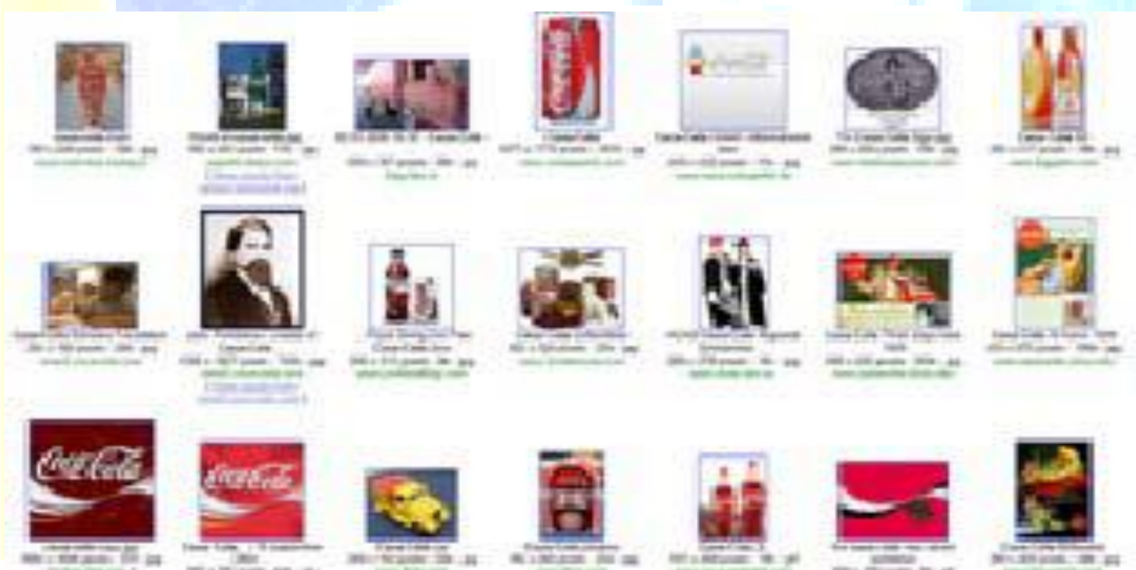
Image search has become a popular feature in many search engines, including Google, Yahoo!, MSN, etc., majority of which use very little, if any, image information[1]. Researchers are actively involved in image search since last decade. Image database is increasing day by day, searching image from large and diversified collection using image features as information to search, is difficult and imperative problem. Image search is an important feature widely used in majority search engines, but the search engine mostly employs the text based image search. Commercial image search engines provide results depending on text based retrieval process. There is no active participation of image features in the image retrieval process; still text based search is much popular. Image feature extraction and image analysis is quite difficult, time consuming and costly process [1]. However, it frequently finds irrelevant results, because the search engines use the insufficient, indefinite and irrelevant textual description of database images.

When a popular image query like "Taj Mahal" is fired, then search engine returns image that occurred on page that contains the term "Taj Mahal". In real sense, locating "Taj Mahal" picture does not involve image analysis and visual feature based search, because processing of billions images is infeasible and increases the complexity level too. For this very reason, image search engine makes use of text based search.

Image searching based on text search possesses some problems like relevance and diversity. When query is fired, less important or irrelevant images appeared on the top and important or relevant images at the bottom of the web page.

For Example, when popular image query like "Taj Mahal" is fired, it provides good image search results but when image query having diversity like "Coca Cola" is fired, searched results provides irrelevant or poor results as shown in Fig.3. Here, required image of Coca Cola can/bottle is seen at the fourth position in the returned images. The reason behind it is large variable image quality [1].

(a) Taj Mahal



(b) Coca Cola

Figure 3: The query for (a) "Taj Mahal" returns good results on Google. However, the query for (b) "Coca Cola" returns mixed results.

1.2 Need and Applications

Google and Yahoo! are two examples of the top retrieval systems which have billions of hits a day. Even though Internet contains media like images, audio and video, retrieval systems for these types of media are rare and have not achieved success as that of text retrieval systems. Image retrieval systems defined as a computer system for browsing, searching and retrieving images from a large database of digital images, are useful in vast number of applications Education and Training, Fingerprint Recognition, Face Recognition, Surveillance system, Home Entertainment, Historic and Art Research, etc. Thus we need a powerful image search engine which will organize and index the images available on web. The database mentioned here can be a small photo album or can be the whole web.

1.3 Semantic Matching

Semantic matching is a technique used in Computer Science to identify information which is semantically related. This approach is based on two key notions, namely:

1) Concept of a label is the set of documents that are about what the label means in the world.
2) Concept at a node is the set of documents that we would classify under this node, given it has a certain label and it is positioned in a certain place in the tree.

Semantic Matching Algorithm

1) Translate natural language expressions into internal formal language
2) Compute concepts based on possible senses of words in a label and their interrelations
3) Extend concepts at labels by capturing the knowledge residing in a structure of a graph in order to define a context in which the given concept at a label occurs.
4) Exploit a priori knowledge, e.g., lexical, domain knowledge with the help of element level semantic matchers
5) Reduce the matching problem to a validity problem

Preprocessing

1) Tokenization: Labels (according to punctuation, spaces, etc.) are parsed into tokens.
2) Lemmatization: Tokens are morphologically analyzed in order to find all their possible basic forms.
3) Building atomic concepts: An oracle (WordNet) is used to extract senses of lemmatized tokens.

4) Building complex concepts: Prepositions, conjunctions, etc. are translated into logical connectives and used to build complex concepts out of the atomic concepts.

Computation

Concept at a node for some node n is computed as an intersection of concepts at labels located above the given node, including the node itself.

1.4 Text Based Image Retrieval (TBIR)

TBIR use methods, which vary from simple frequency of occurrence based method to ontology based method. These are assumed to handle semantic queries more effectively than content based image retrieval systems.

1.5 Content based image retrieval (CBIR)

Image Retrieval system is an effective and efficient tool for managing large image databases. The goal of CBIR is to retrieve images from a database that are similar to an image placed as a query. In CBIR, for each image in the database, features are extracted and compared to the features of the query image. It is a term used to describe the process of retrieving images form a large collection on the basis of features (such as color, texture etc.) that can be automatically extracted from the images themselves. The retrieval thus depends on the contents of images. A CBIR method typically converts an image into a feature vector representation and matches with the images in the database to find out the most similar images.

- "Pure" CBIR systems - search queries are issued in the form of images and similarity measurements are computed exclusively from content-based signals.
- "Composite" CBIR systems - allow flexible query interfaces and a diverse set of signal sources, a characteristic suited for Web image retrieval as most images on the Web are surrounded by text, hyperlinks, and other relevant metadata.

2. Image Ranking & Retrieval Techniques

Image ranking improve image search results on robust and efficient computation of images similarities applicable to a large number of queries and image retrieval. Image retrieval and ranking technique like Topic Sensitive PageRank, Content Based Image Retrieval (CBIR), VisualSEEK, and RankCompete etc. are introduced to enhance the performance of image search.

2.1 Pagerank Algorithm

Sergey Brin et al. ordered web information hierarchy based on link popularity. A page was ranked higher having more links to it and a page links with higher ranked page, become much highly ranked. PageRank concepts within the web pages have the theory of link structure [1]. It assigns a numerical weighting to each element of documents, which measures its relative importance within the set.

2.2 Topic Sensitive Pagerank

The densely connected web pages, through link structure may have higher ranking for the query for which they are not containing resources with useful information. The same web page may have different importance for different query search; it may have higher weightage in one query and less weightage for another. To overcome this, Topic Sensitive PageRank is introduced. In this approach, set of PageRank vector is calculated offline for different topics, to produce a set of important score for a page with respect to certain topics, rather than computing a rank vector for all web pages.[8]

2.3 Content Based Image Retrieval

In CBIR (Content Based Image Retrieval), images are arranged systematically according to their visual feature [9]. Image feature extraction and segmentation are basic steps in CBIR to look for similar images. Image retrieval in CBIR is processed by three ways, in the target search method; pattern matching and object recognition is performed. Image retrieval from large data base with indefinite information is challenging task. The category search method involves object recognition and arithmetic pattern recognition problems. Features selection and classifications from huge number of classes is relatively difficult task. Search by association is the third method, which suffers from semantic gap. Semantic gap is the difference between extracted information from the visual data and its interpretation for a user in a given situation.

Feature of an image involves global or local features. Global features of image contain complete characteristics of entire image and local feature used for a small group of pixels. Global features are very sensitive to location so there is problem in distinguishing forefront and background of image; so it is difficult to decide grade for identifying important visual features. On the other hand, local feature is an image pattern which differs from its immediate neighborhood. To decrease computation, entire image is divided in non overlapping small blocks and features are extracted for each block separately. Thereafter, segmentation is done by k-means clustering or normalized cut criteria [5].

The semantic gap between visual feature and image concept are reducing in CBIR in three ways, which includes supervised and non-supervised learning and relevance feedback approaches. Even though, CBIR system does not fully exploit robust features between image and high-level concept, but also have limited accuracy for certain features.

2.4 VisualSeek

VisualSeek is a crossbreed system, which present a new content based approach. The query results are returned depending on image regions and spatial outline. Spatial features contain size, location and relation- ships to other regions. Each image is divided into small regions which have combination of image feature and spatial properties. The combination depends on the representation of color regions by color sets. One color sets are suitable for predetermined region extraction from side to side color set back projection and other color sets are simply indexed for retrieval of similar color sets. So that unobstructed images are decomposed into near representative images, which provide to efficient spatial query and similar regions images are easily searched [15].

The VisualSeek system utilizes most important image regions and their feature to compare images. The combination of content based and spatial querying provides useful query structure, which allows similar images retrieval for wide variety of color and spatial queries. VisualSeek improve fast indexing and image retrieval by using spatial and feature information for query search.

2.5 VisualRank

VisualRank approach realizes on analyzing the distribution of visual similarities among the images. It apply common visual feature among a group of images and find the highest similarity node from group of images. The similarity is measured by studying an image to image distance function; means the distance between images from same category should be less than that from different categories. Through an iterative procedure based on the clustering approach and PageRank computation, a numerical weight is assigned to each image. This measures its relative importance to the other images being considered, depending on query image that is provided and utilizes those results for image ranking for better results.

VisualRank employs the way to rank images based on the visual hyperlinks among the images. The goal is not to identify the object or their classification, but the finding common visual similarities between images and use of this information, for applying PageRank algorithm to the image ranking. The main two challenges for using common visual theme concept for image ranking are image processing and a mechanism to utilize this information for the purpose of ranking.

2.6 RankCompete

The popularity of digital cameras, camera phones and high capacity memory cards has led to an explosion of digital images on the web, especially in online photo sharing communities. Measuring visual similarity is difficult from diversified photo collections and ranks the images according to their similarity across the entire photo collection.

RankCompete uses generalizes PageRank algorithm for the task of simultaneous ranking and clustering. Because the ranking results make more sense when comparing only the images with similar semantics and the clustering results can also be improved using ranking information since relevant documents are more similar to each other than the irrelevant documents. RankCompete provide good simultaneous ranking and clustering of web photos.

2.7 Comparative Remark

Image searching is popular after introducing PageRank algorithm because it provide good results, but image retrieval is based on text based method so that for diversifies images it provide complex results. To improve the relevancy of image retrieval results number of retrieval techniques are introduced. CBIR uses image features for image retrieval, in Topic Sensitive PageRank number of image feature vectors are calculated offline for different query. VisualSEEK improve fast indexing and provide results based on image regions and spatial outline. VisualRank provide simple mechanism for image search by creating visual hyperlink among the images and employs the way to image ranking for efficient performance. RankCompete uses clustering approach for diversified collections images.

3. Feature Extraction and Representation

Visual Reranking approach requires to extract features of all images which in turn requires image processing and feature creation of each image. Image is represented by global or local features. A global feature represents an image by one multi-dimensional feature descriptor, whereas local features represents an image by a set of features extracted from local regions in the image. Though, global features has some advantages like requires a smaller amount memory, provide speed and simple to work out but provide less performance compared to local features. Local feature extracted and represented by feature detector like Difference of Gaussian (DoG) and feature descriptor like Scale Invariant Feature Transform (SIFT), provide better results with respect to different geometrical changes and are commonly used.

SIFT descriptor provides the large collection of local feature vector from an image, which does not has effect of image rotation, scaling and translation, etc. SIFT contain four major stages; (1) Scale Space extrema finding (2) Key point localization (3) Orientation assignment and (4) Key point descriptor. In the first step, potential interest points are recognized by scanning the image over location and scale. This is implemented efficiently by using difference-of-Gaussian (DoG) images. In the second step, candidate key points are limited to a small area and eliminated if found to be unstable. The third steps, identifies the one or more orientations for each key point based on its local image gradient route. The final stage builds a local image descriptor for each key point, based upon the image gradients in the region around every key point.

The property of all surfaces that describes visual patterns, each having properties of homogeneity is termed as texture. It contains important information about the structural arrangement of the surface. It also describes the relationship of the surface to the surrounding environment. Six visual features that are used in CBIR are: Coarseness, Contrast, Directionality, Regularity, Roughness, Line likeness.

3.1 Pyramid Structure Wavelet Transform (PSWT)

The wavelet-transform transforms the image into a multiscale representation with both spatial and frequency characteristics. This allows for effective multi-scale image analysis with lower computational cost. Wavelets are finite in time and the average value of a wavelet is zero. A wavelet is a waveform that is bounded in both frequency and duration. The pyramid-structure wavelet transform indicate that it recursively decomposes sub signals in the low frequency channels. This method is significant for textures with dominant frequency channels.[2]

3.2 Eigen Vector Centrality

Eigen vector Centrality provides a principled method to combine the "importance" of a vertex with those of its neighbors in ranking. It is defined as the principle eigenvector of a square stochastic adjacency matrix, constructed from the weights of the edges in the graph. In short eigen values are provided by eigen vector centrality.[1]

4. Literature Survey

Content-based image retrieval (CBIR), is any technology that in principle helps to organize digital picture archives by their visual content. By this definition, anything ranging from an image similarity function to a robust image annotation engine falls under the preview of CBIR. In February 1992, a workshop was organized for visual information management systems that would be useful in scientific, industrial, medical, environmental, educational, entertainment, and other applications." [4]. The progress made during 1994–2000 phase was lucidly summarized at a high level in Smeulders et al. [2000], which has had a clear influence on progress made in the current decade, and will undoubtedly continue for future work.

In 2000, Smeulders et al. [3] proposed a fundamental concept and difficulty in CBIR i.e., the semantic gap, which usually is described as the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data has for a user in a given situation,. They separated image retrieval into broad and narrow domains, depending on the purpose of the application. A broad domain includes images of high variability, for instance large collections of images with mixed content downloaded from the Internet. A narrow domain typically includes images of limited variability, like faces, airplanes, etc. The separation into broad and narrow domains is today a well-recognized and widely used distinction [4].

In 1999, W. Ma et al. [5] presented an implementation of NeTra, a prototype image retrieval system that uses color, texture, shape and spatial location information in segmented image regions to search and retrieve similar regions from the database. A distinguishing aspect of this system is its incorporation of a robust automated image segmentation algorithm that allows object or region based search and it also improves the quality of image retrieval when images contain multiple complex objects[5].

In 2002, C .Carson et al. [6] presented a new image representation that provides a transformation from the raw pixel data to a small set of image regions that are coherent in color and texture. The regions are called as Blobworld. This "Blobworld" representation is created by clustering pixels in a joint color-texture-position feature space [6].

In 2002, R. Kondor et al. [11] propose a general method of constructing natural families of kernels over discrete structures, based on the matrix exponentiation idea. They used the ideas from spectral graph theory to propose a natural class of kernels on graphs, which we refer to as diffusion kernels. We start out by presenting a more general class of kernels, called exponential kernels, applicable to a wide variety of discrete objects [11].

In 2002, X. He et al. [9] presented a novel unified framework for structural analysis of image database using spectral techniques, drawing on the correspondence between spectral clustering, spectral dimensionality reduction, and the connections to the Markov Chain theory [9].

In 2003, X. Zhu et al. [12] had put an approach to semi-supervised learning that is based on a Gaussian random field model and proposed a random-walk model on graph manifolds to generate "smoothed" similarity scores that are useful in ranking the rest of the images when one of them is selected as the query image [12]. The resultant learning algorithm has intimate connections with random walks, electric networks, and spectral graph theory [12]. The goal is not classification; instead, it models the centrality of a graph as a tool for ranking images.

In 2004, Fergus et al. [8] proposed a visual filter which reranks the images that are obtained through the commercial search engine. This filter is based on 'visual consistency' obtained from the observation that the images are related to the search typically which are visually similar, while images that are unrelated to the search will typically look different from each other as well[8].

In 2006, D. Joshi et al. [7] presented a story picturing engine, where the user has to enter the story, from which the keywords are selected. Depending on those keywords, pictures about each concept mutually reinforce the best pictures among them termed as candidate images. The level of reinforcement depends upon their mutual similarity values. Integrated Region Matching

(IRM) is used for image matching. Then the final output is ranked images by reinforcement ranking [7].

In 2007, W. Zhou et al. [13] define the canonical image as those that contain most important and distinctive visual words. They proposed to use latent visual context learning to discover or measure visual word significance and develop Weighted Set Coverage algorithm to select canonical images containing distinctive visual words. In order to construct a good candidate image pool and filter some noisy images, they also propose an image link graph to rank all images and select the top ones for canonical image selection [13].

In 2007, B.J.Frey et al. [10] recently proposed affinity propagation algorithm and also attempts to find the most representative vertices in a graph. Instead of identifying a collection of medoids in the graph, VisualRank differs from affinity propagation by explicitly computing the ranking score for all images. Several other studies have explored the use of a similarity-based graph [11], [12] for semi supervised learning.

In 2003, Zhu et al. [12], proposed another related work using a random-walk model on graph manifolds to generate "smoothed" similarity scores that are useful in ranking the rest of the images when one of them is selected as the query image. The approach is one which differs from that in [15] by generating an a priori ranking given a group of images. The work is closely related to [10], as both explore the use of content-based features to improve commercial image search engine. Random-walk-based ranking algorithms were proposed in [9], [7] for multimedia information retrieval. This work is also an extension of that in [12] in which image similarities are used to find a single most representative or "canonical" image from image search results.

The VisualRank is an extension of [12], [13], which is an end-to-end system, to improve Google image search results with emphasis on robust and efficient computation of image similarities applicable to a large number of queries and images.

5. Proposed Approach

The aim of proposed approach is to reduce the number of irrelevant images acquired as the result of image search and provide quality consistent output. Also, the objective is to perform text based search on database to get ranked images and extract texture features of them to obtain reranked images by visual search.

The proposed approach relies on analyzing the distribution of visual similarities among the images and image ranking system that finds the multiple visual themes and their relative strengths in a large set of images. "Visual filters" can be used to rerank search results images, bridging the gap between "pure" CBIR systems and text-based commercial search engines.

Unlike many classifier based methods, that construct a single mapping from image features to ranking, visual reranking relies only on the inferred similarities, not the features themselves. One of the strengths of this approach is the ability to customize the similarity function based on the expected distribution of queries.[1]

In order to improve the efficiency of database images, pyramid-structured wavelet transform can be used along with eigen vector centrality.

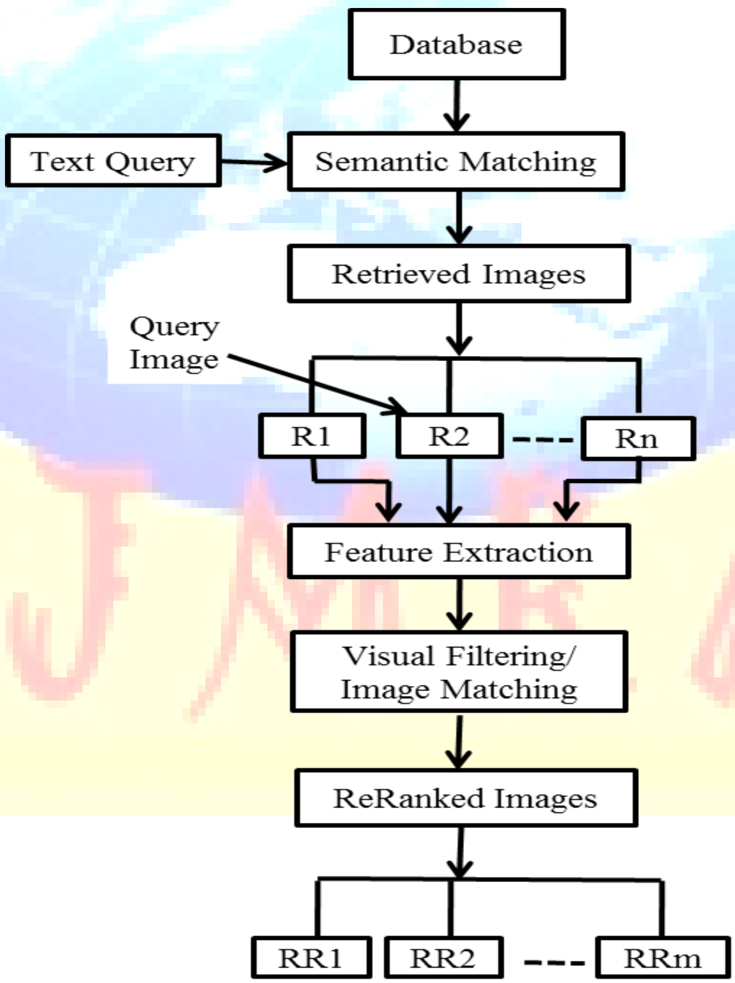


Figure 4: Block diagram of proposed approach.

5.1 Visual Reranking Approach

Visual search approach has proven unsatisfying as it often entirely ignores the visual content itself as a ranking signal. To address this issue, visual search reranking has received increasing attention which is defined as reordering of visual images based on their visual appearance to improve the search performance. The re-ranking process is used to improve the search accuracy by reordering the images based on the multimodal information extracted from the initial text based search results, the auxiliary knowledge and the example image. The auxiliary knowledge can be the extracted visual features from each images or the multimodal similarities between them.

6. Conclusion

This paper presents a survey on image ranking, which is important part of image retrieval from large scale web-images and also a simple mechanism to incorporate the advances made in using link and network analysis for Web document search into image search. Image retrieval techniques including conventional PageRank algorithm with Topic Sensitive PageRank, CBIR and VisualSEEK for better performance of web-image retrieval are discussed. PageRank provide standards for quality measurement of web-page, but it favors older pages of website. More accurate image retrieval results are returned by Topic Sensitive PageRank. CBIR provides much relevant results and reducing semantic gap up to certain level. Also, VisualRank approach is one where image get higher ranking, because their similarities matches are more than others, based on common visual similarities present in link structure of web.

Along this VisualRerank approach is discussed, which allows reordering of visual images based on their visual appearance to improve the search performance. Also, to improve the search accuracy by reordering the images based on the multimodal information extracted from the initial text based search results, the auxiliary knowledge and the query example image. Addition of supplementary local and sometime global feature may offer better image retrieval results.

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