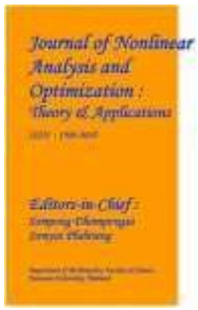
Journal of Nonlinear Analysis and Optimization
Vol. 16, Issue. 1: 2025
ISSN : 1906-9685



Similarity Search towards Encrypted Images for Content - Based Image Retrieval in Cloud Computing

KASANI ANJALI[1], Dr. B. V. RAM KUMAR[2], Dr. G. SATYANARAYANA[3]

#1 M.Tech Scholar and Department of Computer Science Engineering,
#2 Professor, Department of Computer Science and Engineering, DNR College Of Engineering and Technology, Bhimavaram, AP, India.
#3 Professor, HOD Department of Computer Science and Engineering, DNR College Of Engineering and Technology, Bhimavaram, AP, India.

Abstract:

Content-based image retrieval (CBIR) applications have been rapidly developed along with the increase in the quantity, availability and importance of images in our daily life. However, the wide deployment of CBIR scheme has been limited by its the severe computation and storage requirement. With the emergence of intelligent terminals, the Content-Based Image Retrieval (CBIR) technique has attracted much attention from many areas (i.e., cloud computing, social networking services, etc.). Although existing privacy-preserving CBIR schemes can guarantee image privacy while supporting image retrieval, these schemes still have inherent defects (i.e., low search accuracy, low search efficiency, key leakage, etc.). To address these challenging issues, in this paper we provide a similarity Search for Encrypted Images in secure cloud computing model are used to improve search accuracy which can improve search efficiency. Finally, it is extended to further prevent image users' search information from being exposed to the cloud server. Our formal security analysis proves that can protect image privacy as well as key privacy. The security analysis and experiments show the security and efficiency of the proposed scheme.

KEYWORDS: Image search, image re-ranking, semantic space, semantic signature, keyword expansion, one clicks feedback.

I. Introduction:

The majority of web picture web indexes use decisive words as questions and depend On the content to pursuit pictures. In this manner, experience the ill effects of the equivocalness of inquiry catchphrases, on the grounds that it is hard for clients to precisely characterize the visual substance of target picture just utilizing decisive words. Case in point, utilizing "Mac" as a question decisive word, the recovered pictures have a place with distinctive classes additionally called ideas in this paper, for example, "red Macintosh," "Mac logo," and "Mac tablet." keeping in mind the end goal to explain the uncertainty, diverse procedures are is generally utilized. In the system explored in this paper, an inquiry magic word is initially used to recover an arrangement of pictures. At that point the client is requested that select a picture from these recovered pictures. Likewise, the staying of the pictures is positioned in light of their visual similitudes. The significant test is the connection of similitudes of visual components and pictures' semantic importance, which are expected to decipher clients' aim to seek. As of late, it has been proposed to match pictures in a semantic space that utilized properties or reference classes firmly identified with the semantic implications of pictures as premise. On the other hand, describing the profoundly different pictures from the web is troublesome in light of the fact that it is difficult to take in a widespread visual semantic space. The fundamental goal of this paper is to give precise result in light of catchphrase and additionally contrasting the semantic marks of pictures with give re-positioned pictures to the clients. Inquiry Specific Semantic Signatures method gives the correct approach to seek the web pictures. 2. Writing Survey Recently, for general picture acknowledgment and coordinating, there have been an alternate deal with utilizing projections over predefined ideas, qualities or reference classes as picture marks. The classifiers of ideas, traits, and reference classes are prepared from known classes with samples. In any case, the information gained from the known classes can be exchanged to perceive tests of novel classes which have few or even no preparation tests. Since these ideas, traits, and reference classes are characterized with semantic implications, the projections over them can well catch the semantic implications of new pictures even without further preparing. Rasiwasia et al. [2] mapped visual elements to an all-inclusive idea word reference for picture recovery. Traits with semantic implications were utilized for article location and acknowledgment, face acknowledgment, activity acknowledgment, picture hunt and 3D item recovery. Lampert et al. [3] predefined an arrangement of properties on a creature database and distinguished target items in view of a blend of human-determined traits as opposed to preparing pictures. Parikh and Grauman [4] proposed relative ascribes to demonstrate the quality of a property in a picture concerning different pictures. Some methodologies exchanged information between item classes by measuring the similitudes between novel article classes and known article classes called reference classes. Case in point, Torresani et al. [5] proposed a picture descriptor which was the yield of various classifiers on an arrangement of known picture classes, and utilized it to match pictures of other inconsequential visual classes.

II. Related Work:

Substance based picture recovery utilizes visual elements to ascertain picture comparability. Pertinence input was generally used to learn visual closeness measurements to catch clients' pursuit expectation. Notwithstanding, it obliged progressively clients' push to choose numerous important and immaterial picture cases and frequently needs web preparing. For a web-scale business framework, clients' criticism must be constrained to the base with no web preparing. Cui et al. proposed a picture re-positioning methodology which restricted clients' push to only a single tick input. Such basic picture re-positioning methodology has been received by prominent webscale picture web indexes, for example, Bing and Google as of late, as the "discover comparable pictures" capacity. The key part of picture re-positioning is to figure the visual similitudes between pictures. Numerous picture elements have been produced as of late. On the other hand, for distinctive question pictures, low-level visual elements that are compelling for one picture classification may not function admirably for another. To address this, Cui et al. grouped the inquiry pictures into eight predefined aim classes and gave distinctive element weighting plans to diverse sorts of question pictures. On the other hand, it was troublesome for just eight weighting plans to cover the huge differing qualities of all the web pictures. It was likewise likely for a question picture to be ordered to a wrong class. As of late, for general picture acknowledgment and coordinating, there have been various takes a shot at utilizing predefined ideas or characteristics as picture mark. Rasiwasia et al. mapped visual components to a widespread idea lexicon. Lampert et al. utilized predefined credits with semantic implications to identify novel article classes. Some methodologies exchanged information between article classes by measuring the likenesses between novel item classes and known article classes (called reference classes).Every one of these ideas/characteristics/reference-classes were all around connected to every one of the pictures and their preparation information was physically chosen. They are more suitable for logged off databases with lower differences, (for example, creature databases and face databases) such that question classes better share similitudes. To model all the web pictures, a gigantic arrangement of ideas or reference classes are obliged, which is unrealistic and inadequate for online picture re-positioning.

III. Techniques for Image Re-ranking:

Computing the visual similarity that shows the semantic relevance of images which is the key component of image reranking. Many visual features have been developed in recent years. However, the effective low-level features are different for different query images. Therefore, Cui et al. [6], [7] classified the query images into eight predefined categories and gave different feature weighting schemes to different types of query images. But to cover the large diversity of all the web images was difficult for the eight weighting schemes. And also possibility of query image to be classified to a wrong category. Query-specific semantic signature was first proposed to reduce the semantic gap. There is a lot of work on to re-rank images which are retrieved by initial text-only search using visual features, however, without requiring users to select query images. Jing and Baluja proposed Visual Rank to analyze the visual link structures of images and to find the visual themes for re-ranking. Cai et al. re-ranked images with attributes which were manually defined and learned from manually labeled training samples. These approaches assumed that there was one major semantic category under a query keyword. Images were re-ranked by modeling this dominant category with visual and textual features

.

Re-Ranking without Query Images

Query-specific semantic signature can be applied to image re-ranking without giving query images. This application requires the user to input a query keyword. But it assumes that images returned by initial text-only search have a given topic and images belonging to that topic should have higher ranks. This approach typically addresses two issues:
(1) how to compute the similarities between images and reduce the semantic gap between them; (2) how to find the dominant topic with any ranking algorithms based on the similarities of images. The query-specific semantic signature is effective in this application since it can improve the similarity measures of images and also it is crucial to reduce the semantic gap when computing the similarities of images. Due to the ambiguity in query keywords, there may present multiple semantic categories under one keyword query. These approaches cannot capture user’s search intention accurately without query images selected by users.

IV. Conventional Image Re-Ranking Framework:

Major web image search engines have adopted one-click feedback strategy [8]. It is an effective way to improve search results and its interaction is simple enough. Its diagram is shown in Fig. 1. Given a query keyword input by a user, a bunch of images relevant to the query keyword is retrieved by the search engine according to a stored word-image index. The size of the returned image pool is fixed, e.g., containing 1000 images.

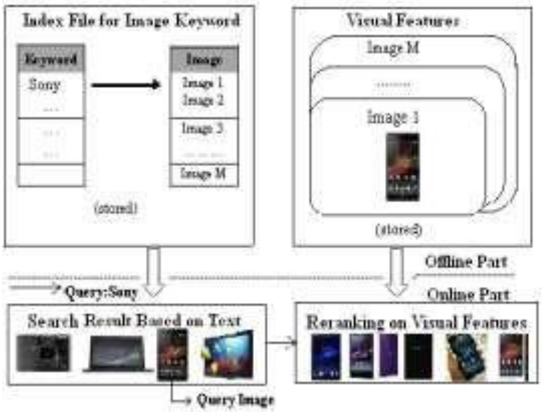


Fig: The conventional image re-ranking framework

The user is asked to select a image which is query from the pool of image. This image tells the user's search intention and the remaining images in the pool are re-ranked based on their visual similarities with the given query image. The word-image index file and visual features of images are pre computed and stored at offline stage. The main online computational work is comparing visual features. To achieve good efficiency, the visual feature vectors need to be short and their matching needs to be fast. Some visual features are in high dimensions and efficiency is not satisfactory if they matched directly. In this approach, reference-classes are applied to all the images and they are defined manually. They are suitable for offline databases such as animal data-bases and face databases, since image classes in these databases may share similarities in a better way.

V. Keyword Expansion

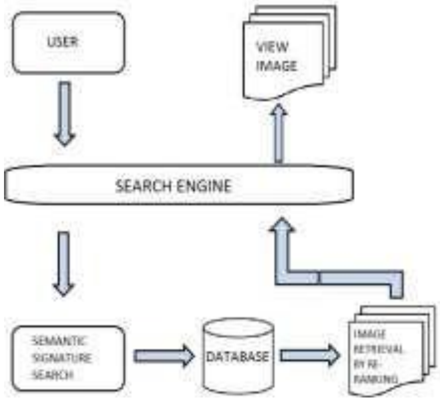
For a keyword q, we automatically define its reference classes through finding a set of keyword expansions E(q) most relevant to q. To achieve this, a set of images S(q) are retrieved by the search engine using q as query based on textual information. Keyword expansions are found from the words extracted from the images in S(q)3. A keyword expansion e belongs to E(q) is expected to frequently appear in S(q).In order for reference classes to well capture the visual content of images, we require that there is a subset of images which all contain e and have similar visual content. Based on these considerations, keyword expansions are found in a search-and-rank way as follows. For each image I belongs to S(q), all the images in S(q) are reranked according to their visual similarities to I. The T most frequent words WI = {w1I ;w2I ; _ _ _ ;wTI} among top D re-ranked images are found. If a word w is among the top ranked image, it has a ranking score rI (w) according to its ranking order; otherwise rI (w) = 0, rI (w) =T - j w = wjI rI (w) =0 w not belongs to WI..................(1) The overall score of a word w is its accumulated ranking scores over all the images, r(w) =summation of(I2S) rI (w) … (2) The P words with highest scores are selected and combined with the original keyword q to form keyword expansions, which define the reference classes.

VI. SEMANTIC SIGNATURES

Given M reference classes for keyword q and their training images automatically retrieved, a multi-class classifier on the visual features of images is trained and it outputs an M-dimensional vector p, indicating the probabilities of a new image I belonging to different reference classes. Then p is used as semantic signature of I. The distance between two images Ia and Ib are measured as the L1-distance between their semantic signatures pa and pb, d(Ia; Ib)=|| pa - pb||1.

VI. Intelligent Semantic Web Search

We propose the semantic web-based search engine which is also called as Intelligent Semantic Web Search Engines. Here we propose the intelligent semantic web-based search engine and we use the power of xml meta-tags deployed on the web page to search the queried information. The xml page will be consisted of built-in and user defined tags. The metadata information of the pages is extracted from this xml into rdf. Practical results showing that proposed approach taking very less time to answer the queries while providing more accurate information



"Fig.", Shows the Architecture diagram.

In this above diagram Fig., when the user enters the query keyword the search engine searches the image based on the semantic signature assigned to that image while uploading. It then fetches the images from database using semantic signatures and re-ranks the image based on the one click feedback given by the user. The retrieved images are then displayed into the semantic space allocated for this. And then the images are viewed by the user. When the user clicks the particular image displayed in the semantic space the image will be displayed for download. Augmented image is displayed for each category in the same page where the image is available for download. In order to download the image, the user has to login and then have to download. There are many modules in this. For admin, it has authentication, upload files, signature file, and visual correlate. For user, it has authentication, Search engine, view files, and information retrieval (augmented image). Visual correlate: If the admin uploads the same image more than once then it can remove the duplicate images and keep the original image alone. The duplicate images are removed by cross checking with the image size and file name.

VII. PROPOSED SCHEMA:

NEW IMAGE RE-RANKING FRAMEWORK

The diagram of new image re-ranking framework is shown in figure . The reference classes which are used to represent different semantic concepts of query keywords are automatically discovered at the offline stage. Therefore, by considering both textual and visual information, a set of most appropriate or relevant keyword expansions are automatically selected for a given query keyword. For example, "Sony" as a keyword then a set of most relevant keyword expansions such as "Sony laptop", "Sony handsets", "Sony TV" and "Sony digital camera" are automatically selected. The reference classes of a query keyword are defined by this set of keyword expansions. If we want to automatically obtain the training example of reference class then the keyword expansion (e.g. "Sony laptop") is used to retrieve images by the search engine. Instead of images are retrieved by the original keyword, if those are retrieved by the keyword expansion then these are much less different. The top retrieved images are used as the training examples of the reference class after removing the outliers automatically. There are some reference classes which have similar semantic meanings as well as their training sets are visually similar. For example, "Sony handset" and "Sony mobile". Therefore, redundant reference classes are removed, in order to improve the efficiency of online image re-ranking.

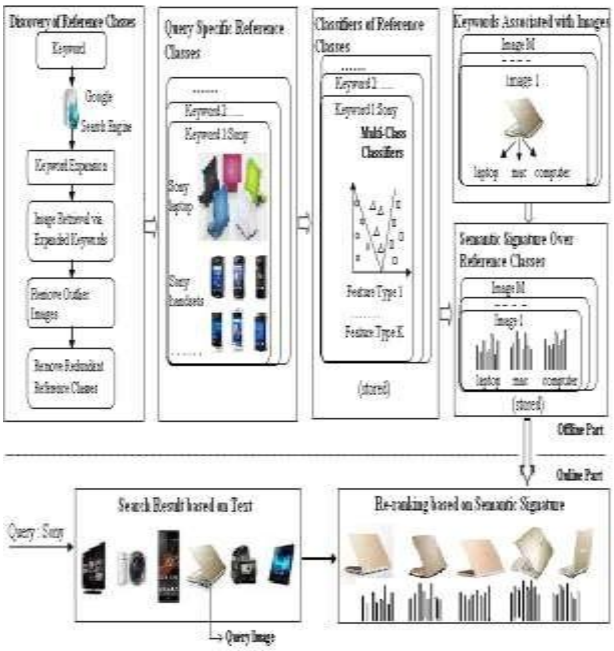


Fig. New image re-ranking framework

A multi-class classifier on low level visual features for each query keyword is trained from the training sets of its reference classes which is stored offline. If there are multiple types of visual features then one could combine them to train the single classifier. Due to this, it can increase the re-ranking accuracy but will also increase storage as well as reduce the online matching efficiency because of the increased size of semantic signatures. Most of the time, images are relevant to the multiple query keywords. Therefore, it could have several semantic signatures which are obtained in different semantic spaces. Each image which is stored in the database is associated with a few relevant keywords, according to the word image index file. By computing the visual similarities between the image and the reference classes of the keyword, a semantic signature of the image is extracted for each relevant keyword. There are N semantic signatures to be computed if an image has N relevant keywords, and stored offline.

VIII. CONCLUSION & FUTURE WORK:

A unique re-ranking framework is proposed for image search on internet in which only only one-click as feedback by user. Specific intention weight schema is used proposed to combine visual features and visual similarities which are adaptive to query image are used. The feedback of humans is reduced by integrating visual and textual similarities which are compared for more efficient image re-ranking. User has only to do one click on image, based on which re-ranking is done. Also, duplication of images is detected and removed by comparing hash codes. Image content can be compactly represented in form of hash code. Specific query semantic spaces are used to get more improvised re-ranking of image. Features are projected into semantic spaces which are learned by expansion of keywords.

In this paper, we have reviewed a novel image re-ranking framework by learning the query-specific semantic spaces it helps to significantly improve both the effectiveness and efficiency of online image re-ranking. At offline stage, through keyword expansions the visual features of images are projected into their related visual semantic spaces automatically. We have also discussed the conventional image search techniques and find out their drawbacks. The reviewed image re-ranking framework overcomes the drawbacks of existing method and improves search result as per user's intention.

REFERENCES:

[1] E. Bart and S. Ullman. Single-example learning of novel classes using representation by similarity. In Proc. BMVC, 2005.

[2] Y. Cao, C. Wang, Z. Li, L. Zhang, and L. Zhang. Spatial-bag-of features. In Proc. CVPR, 2010.

[3] B. Luo, X. Wang, and X. Tang. A world wide web-based image search engine using text and image content features. In Proceedings of the SPIE Electronic Imaging, 2003.

[4] J. Cui, F. Wen, and X. Tang, "Intent Search: Interactive On-Line Image Search Re-Ranking," Proc. 16th ACM Int'l

Conf. Multimedia, 2008.
[5] J. Cui, F. Wen, and X. Tang, “Real Time Google and Live Image Search Re-Ranking,” Proc. 16th ACM Int’l Conf. Multimedia, 2008.
[6] D. Lowe. Distinctive image features from scale-invariant key points. Int’l Journal of Computer Vision, 2004.
[7] C. Lampert, H. Nickisch, and S. Harmeling. Learning to detect unseen object classes by between-class attribute transfer. In Proc. CVPR, 2005.
[8]J. Philbin, M. Isard, J. Sivic, and A. Zisserman. Descriptor Learning for Efficient Retrieval. In Proc. ECCV, 2010.

Authors

Kasani Anjali, Pursing M.Tech in Department of Computer Science and Engineering from D.N.R College of Engineering & Technology,Bhimavaram, Andhra Pradesh ,West Godavari, 534201,India. Done MCA in B.V Raju college of Engineering, Bhimavaram. Her area of Interest includes cloud computing.

Dr. B V Ram Kumar M.E, Ph.D. is working as a Professor, Department of Computer Science and Engineering, DNR College Of Engineering and Technology, Bhimavaram, West Godavari District, Andhra Pradesh, India, with an experience of 23 years.

Dr. G. Satyanarayana is working as a Professor and HOD in the Department of Computer Science and Engineering, DNR College Of Engineering and Technology, Bhimavaram, West Godavari District, Andhra Pradesh, India