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A Review of Image Searching Using Hash Code Techniques

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Abstract-The hashing techniques have been attracting huge attention in images search due to easy availability of very big amounts of data in present scenario. In this paper, various image search techniques using different hashing methods are reviewed. More than a few hashing methods such as state of the art which is used to generate hash codes, then embed and extract features of images in the high-dimensional form. This scale image search can be performed in real time; this is based on Hamming distance. This procedure consists of weighted Hamming distance and finer-grained ranking. Query adaptive weights consist of semantic concept classes which improves the result of an image search. With the Query adaptive bit weights, images are ranked and calculated by weighted Hamming distance.

Keywords-Query-adaptive image search, scalability, hash codes, weighted Hamming distance, Query-adaptive ranking, binary code, image search.

I. INTRODUCTION

The capability of interested standardized images in immensely huge databases has great potential in many authentic-world applications. While conventional image search engines heavily rely on textual words associated with the images, scalable contented predicated search techniques are receiving incrementing attention and have recently appeared in some search engines such as Google and Bing. Apart from providing more preponderant image search experience for common place users on the web, scalable homogeneous image search has additionally been shown to be secondary to solving traditionally very conundrum in computer vision.

The most popular concept that is feature extraction, in this one can select the most significant attributes and combining attributes into a new reduced set of features. Feature extraction involves reducing the amount of resources required to describe a large set of data. It is found that a Bag of visual Words (BoW), and Scale Invariant Feature Transform (SIFT) invariant image descriptors are used to extract and quantized a large set of data. A Bag of visual words is a vector of occurrence counts of a vocabulary of local image features. These vectors of occurrence counts are called feature descriptors. A good descriptor should have the capability to hold intensity, rotation, scale and even vary to some extent. One of the most famous descriptors is a SIFT, this descriptor is embedded and extract the features [1].

Hashing is preferable over tree-predicated indexing structures as it generally requires greatly reduced recollection and additionally works more preponderant for high-dimensional samples. With the help of compact binary codes similar Hamming space can be measured by Hamming distance and an integer value is obtained. To measured Hamming distance there is use of XOR process, and search Hamming space between zero to hundred. From the previous results, hundreds or more than thousands of images having same ranking in search end result list, but mostly they are not possible to be consistently related to the query [6].

To computes the similar images obtained exact ranking as well as it persistently increases, but at the same time there is need of some space and memory. For this, there is one novel approach that is Query adaptive weights. In this concept, it consists of weights for each bit of hash codes. By using this conception, images are ranked on finer grained hash code level with the help of bitwise weight. At the time of generation of hash code each hash code having unique similarities between the queries. In authentic-time there is a strong need to be computed query-adaptive bitwise weights. At this time, it develops a set of semantic concept classes that cover many semantic aspects of image content such as scenes and objects. With the help of this technique one of the finest weights can be computed by iteratively solving quadratic programming quandaries. These pre-computed class-categorical bitwise weights are then utilized for online computation of the query-adaptive weights, through quickly evaluating the closeness of a query image to the image samples of the semantic classes. To evaluate the correlated attributes between the query and given images in a target database there is need to apply weighted hamming distance [4], [6].

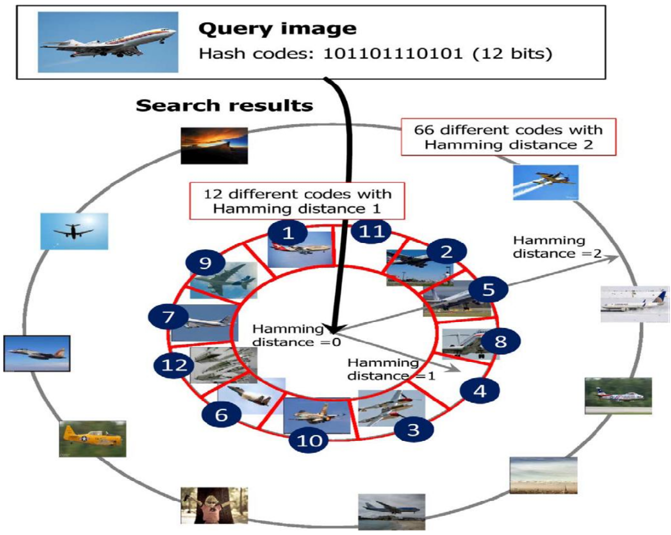

Figure 1. Query-adaptive image search approach[1]

Figure 1shows that the projected approach of Query-adaptive image searches in which it represents 12 bit hash code. The specified example shows the result of hashing based search. In this it shows the integer value of Hamming distance, in many hash code shares the same distance to the query. One can observe that 12 bit hash code have Hamming distance 1. Also differentiate the ranking of the 12 bit hash codes [1].

II. RELATED WORK

There are various techniques that are recently developed in order to classify the query adaptive image search. These techniques provide guidelines for improving the existing technique for finding more appropriate learning technique. The popular bag-of-visual-words (BoW) are based on memory usage per image. HerveJegou *et al* .proposed BoW reduces memory usage by more than one order of magnitude. At the time of rank the images a distance expectation criterion is then used and at least one order of magnitude faster than standard bag-of-features while providing excellent search quality. In BoWthey used SIFT descriptors and their geometry information in which they consist of the location, orientation, and size of the image patch from which the descriptor was extracted. For each descriptor, their method retrieves the nearest local invariant image descriptor in a large-scale image database using nearest neighbor search[3].

Wei Liu *et al*.proposed a scalable graph-based unsupervised hashing approach which respects the underlying manifold structure of the data back to nearest neighbors Their Experimental results shows significant presentation gain the state of the art hashing methods in retrieving semantically related neighbors [5].

There are various hashing methods which can be used in image searching for improved results. The most presented techniques are supervised and unsupervised; along with this the Locality Sensitive Hashing(LSH) improves online selection of pool hash function. In this way the accuracy of the search is improved [9].

HerveJegou*et al*. proposed enhanced LSH by the stageofon-line selection of the hash functions from a pool of functions. A further enhancement originates from the use of E8 lattices for geometric hashing instead of one-dimensional random projection. A performance based on state of the art high-dimensional descriptors compute on real images shows improvements onLSH to decrease the search complexity for a given level of accuracy. Motivated by this Y. Weiss *et al*., proposed a spectral hashing (SH) method, in this input space based depends on data distribution for hashing. Spectral hashing is used to discover a finest code for a certain dataset which is associated with the graph [8].In Locality Sensitive Hashing (LSH) is a most prominent method, this engender each hash bit typically by projecting the data points to an arbitrary hyper plane and then conducting arbitrary threshold. Spectral hashing ascertains that the projections are orthogonal and sample number is balanced across different buckets. All these methods are used to search approximate nearest neighbor search [10].

There are specified hashing methods such as unsupervised and supervised. The unsupervised hashing method shows better results than the supervised hashing. H. Jegou*et al*., proposed the unsupervised hashing gives performance in the form of labeled pairs of images. The supervised hashing method consists of the most popular methods such LSH, and Spectral hashing, having a great effect on supervised hashing. Unsupervised hashing performs labeled pair of images, where semi supervised hashing is used to minimize the error on the labeled data and images [11].

Yu-Gang Jiang *et al*. proposed query adaptive image search using hamming distance which shows finer grained ranking on image search. In this method the weighted Hamming distance using hash codes is generated. The generated hamming distance is assigned by each bit of hash code. They consider the learning class specific weights algorithm which is used to quickly compute query adaptive weights from semantic concept classes. The Hash code is generated by two methods that are Semi Supervised Hashing and Semantic Hashing with Deep Belief Networks. Here semi-supervised Hashing is used for binary embedding and Semantic Hashing with Deep Belief Networks is used for dimensionality reduction [11].

T. S. Chua *et al*.worked on the semantic concept classes which most widely used NUSWIDE dataset. This technique consists of scenes and objects, here NUSWIDE consist of flicker images, training set images and test set images. The concepts in NUSWIDE are extremely appropriate for constructing the semantic database. Hence NUSWIDE is suitable for all databases[12].

III. METHODOLOGY

Now, we discuss about implementation of above discussed techniques. The objective of Query adaptive image search is used to improve image search techniques using different hashing methods. For this we can distinguish several methodologies for improved image search.

1. Feature Extraction

In this technique, representation of images is shown in the form of popular bag-of-visual-words (BoW) framework in which it represents the frequency of word occurrence detect interest point features, also it finds the closest visual word to the region around detected points largely unaffected by the position and orientation of objects in the image. The local invariant image descriptor represent each region by a SIFT descriptor which build a visual vocabulary by k-means clustering and assign each region to the nearest cluster center are extracted and quantized based on a set of visual words [3].Here the BoW features are then embedded into compact hash codes for capable search [4]. For this approach, consider the hashing method, i.e. state of the art which includes semi supervised hashing for binary embedding and semantic hashing with deep belief networks for dimensionality reduction [9].

2. Hashing

For this method there are different types of hashing methods such as Locality Sensitive Hashing (LSH), this is used to improve online selection of hash function. Another method is spectral hashing (SH);this is used for finding best hash code for data distribution. Here consider two state-of-art hashing techniques, which are also used for embedded the features [8], [11].

2.1 Semi Supervised Hashing

In hash code technique a novel approach is used that is semi supervised hashing (SSH). This method for all intents and purposes used for embedding the image features. In this method, semi supervised hashing (SSH)consists of two major hashing functions that are supervised and unsupervised hashing. Here supervised hashing is used for impractical fitness also it consists of a small amount of labeled data. Unsupervised hashing is generally used for regularization of theoretic information. The unsupervised hashing method does not require any amount of labeled data. However, their parameters are easy to learn a specified predefined matrix. For overcoming the problem related to supervise hashing and unsupervised hashing Jun Wang *et al.*Proposed semi supervised hashing method in this the semantic similarity between labeled data is discussed. Semi supervised hashing is embedded all image features such as testing, training and flicker images. Semi supervised hashing is faster than semantic hashing. Also, it can influence semantic similarity using labeled data. There is one problem with semi supervised hashing is, it is data dependent projection, butJun Wang *et al.*provides some recovered formulation and overcome that problem [9].

2.2 Semantic Hashing with Deep Belief Network

The good quality hash code consists of label images during training phases. Since same images are with the same labeled are hashed into same sections. Deep Belief Network (DBN) is used to reduce the number of units and also reduce the dimension from images. Basically DBN is structured as a graph (directed acyclic graph), in this each node represents a stochastic variable [10].

3. Query Adaptive Search

One of the important methods for improved image searching is the query adaptive image search technique. To get better result, the Hamming distance method is used. Before that, we focus on the framework of query adaptive image search technique [1]

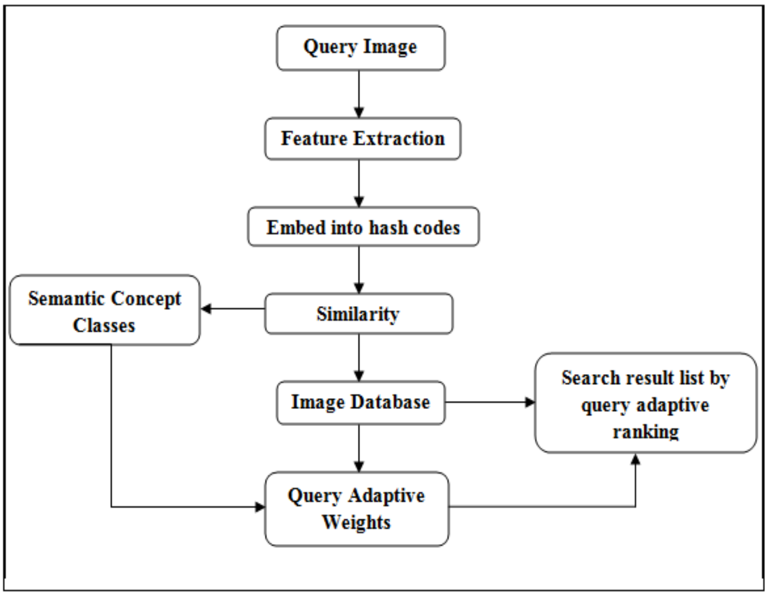

Figure 2. Framework of Query adaptive image search [1].

3.1 Finding Hamming Distance

This is a superior technique for image search i.e. Hamming distance method. Here the Hamming distance is calculated using Hamming space. In this method, Yu-Gang Jiang *et al*. used traditional matrix method called as Euclidean is used for finding Hamming distance. Hamming distance is an integer value and it is generated by finding the distance between two hash codes and total number of bits as shown in fig.1. Here it measures the distance from one hash code to another and these are total number of bits, butt rest generated binary values are different every time. For example, take three different hash codes, i.e. A=1010, B=1100 and C=0000. Hence it calculates the Hamming distance of A and B which is equal to that A and C But the fact is A is differs from B, and B differs from C due to one or two bits. Practically Hamming distance share the distance when all values are same, but in this case there are slight differences in hamming distance. In this technique, perform is depends on the XOR operation and weighted Hamming distance. Here the Hamming distance is calculated in between zero to hundred as shown in fig.1 [1], [6].

4. Query Adaptive Weights and Ranking with Hash Code

In this section, we discuss the operation performed on hash code selection, finding weighs and ranking the images.

4.1 Query Adaptive Hash Code Selection

In the hash code selection technique, a query-adaptive hashing technique is capable to construct the large amount suitable binary code for dissimilar queries. Particularly, a set of semantic biased discriminate projection matrices first finds out about each of the semantic concepts, throughout which a semantic adaptable hash function set first finds out via a joint sparsely variable selection model. The above approach is considered to utilize a single set of common hash codes for image search. In this section, there is use of various cases and several sets of hash codes are available. Since there are several semantic concept classes are used as mentioned in fig. 2, it is extremely simple to train a set of the hash codes for every class by expansively using images containing the resultant concept. The classspecific hash codes are predictable to be additional discriminating for an exacting class of images. At the time of online search, the semantic database is not used only for computing query adaptive weights, but also to decide on a suitable set of class specific hash codes for every query. The semantic concept classes are used to suppose query semantics, which helps us for the collection of a good quality set of hash codes for the query, and the calculation of matching query adaptive weights on the chosen hash codes. The selected Class specific codes are used collectively with the common codes for image search [1], [2], [4].

4.2 Query Adaptive Weights

Query adaptive weighted hash uses the weighted Hamming distance to calculate the distance between hash codes. In this technique there misrepresentation of a weighted Hamming distance and it is calculate by learning the weights from the query information. Particularly, the approach learns class-specific bit weights as mentioned in figure 2. Thus the weighted Hamming distance between the hash codes belong the class and the center that indicatethe hash codes are minimized. The weight for specific query is the standard weight of the weights of the classes that the query most likely belongs to and that are open to the elements in the top similar images were all images are connected with a semantic label.By using Query adaptive weights the images are ranked also generate a unique hash code for each bit of the query image [1], [2].

4.3 Query Adaptive Ranking

The query adaptive ranking method is an initial ranking method with weighted hamming distance. By exploiting the relatives attribute connecting the query and database samples, now study a set of query-adaptive bitwise weights that differentiate together the discriminating authority of each hash function and their balance for most contiguous neighbor search. Transfer different weights to the individual hash bit will differentiate the consequences allotment the same hamming distance, and get an additional fine-grained and accurate ranking order. To estimate how much performance increase using specified query adaptive Hamming distance and hash code selection use both SSH and DBN method with the help of given labeled data. In this section give ranking on the basis of Query adaptive weights as shown in fig. 2. After extraction of images and generation of hash codes given system matching all the similarities and search in image database then it gives the Query adaptive weights [9], [11].

CONCLUSION AND FUTURE WORK

In this paper, different hashing techniques for query adaptive image search have been reviewed. By this study one can generate hash code for each query image. We also reviewed various feature extraction and embedding methods for generating a better hash code. Our study also discuss about query-adaptive bitwise weight with the help of semantic concept classes. In this the images are quickly ranked on the basis of weighted Hamming distances at a finer-grained. Thus the improved image search techniques and nearest neighbor search technique images are very prompt. In future the performance of image searching techniques can be enhanced by using distributed system along with fault tolerance

REFERENCES

[1] Yu-Gang Jiang, Jun Wang, XiangyangXue, and Shih-Fu Chang, "Query-Adaptive Image Search With Hash Codes," in IEEE Transactions on Multimedia, Vol. 15, No. 2, February 2013.

[2] Y.-G. Jiang, J. Wang, and S.-F. Chang, "Lost in binarization: Query adaptive ranking for similar image search with compact codes," in Proc. ACM Int. Conf. Multimedia Retrieval, 2011.

[3] H. Jegou, M. Douze, and C. Schmid, "Improving bag-of-features for large scale image search," Int. J. Comput. Vision, vol. 87, pp. 191–212, 2010.
[4] J. Wang, S. Kumar, and S.-F. Chang, "Sequential projection learning for hashing with compact codes," in Proc. Int. Conf. Machine Learning, 2010.
[5] W. Liu, J. Wang, S. Kumar, and S.-F. Chang, "Hashing with graphs," in Proc. Int. Conf. Machine Learning, 2011.
[6] R.-S. Lin, D. A. Ross, and J. Yagnik, "Spec hashing: Similarity preserving algorithm for entropy-based coding," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2010.
[7] H. Xu, J. Wang, Z. Li, G. Zeng, S. Li, and N. Yu, "Complementary hashing for approximate nearest neighbor search," in Proc. IEEE Int. Conf. Computer Vision, 2011.
[8] Y. Weiss, A. Torralba, and R. Fergus, "Spectral hashing," in Adv. Neural Inf. Process. Syst., 2008.
[9] J. Wang, S. Kumar, and S.-F. Chang, "Semi-supervised hashing for scalable image retrieval," in Proc. IEEE Conf. Computer Vision and Pattern Recognition, 2010.
[10] H. Jegou, L. Amsaleg, C. Schmid, and P. Gros, "Query adaptative locality sensitive hashing," in Proc. Int. Conf. Acoustics, Speech, and Signal Processing, 2008.
[11] G.Hinton and R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," Science, vol. 313, no. 5786, pp. 504–507, 2006.
[12] T.-S. Chua, J. Tang, R. Hong, H. Li, Z. Luo, and Y.-T. Zheng, "NUSWIDE: A real-world web image database from National University of Singapore," in Proc. ACM Int. Conf. Image and Video Retrieval, 2009.

