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Multiple Query Image Retrieval by Topology Preserving Hashing With EM Ranking

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Abstract— In large data sets Hashing-based similarity search techniques is Popular. To find the neighbors, the neighborhood relationships between its sub-regions and the relative closeness to neighbors of each sub-region is represented by topology. However, most existing hashing methods preserve neighborhood relationships while ignoring the relative neighborhood. Most hashing methods preserve the neighborhood relationship while ignoring the relative neighbor. Good ranking is not provided by the most hashing method, where the same hamming distance is shared by a lot of results. In this paper, we proposed hashing method to solve these two issues. We present three different TPH methods namely linear unsupervised TPH; semi-supervised TPH and kernelized TPH. Particularly, our unsupervised TPH is capable of mining semantic relationship between unlabeled data without supervised information and ranking is done with EM ranking. Multiple - query information retrieval algorithm that combines Pareto front method (PFM) with efficient manifold ranking (EMR).

Keywords: EMR, Pareto points, approximate nearest neighbor search, binary hashing, topology preserving hashing, EM ranking

I. INTRODUCTION

Content-based image retrieval (CBIR) is popular for image retrieval [1]. In this paper, we proposed an algorithm for multiple query image retrieval uses topology preserving hashing (TPH) with EM ranking. The HOG method is used for finding the dissimilarity between the samples. The first step in our method is to rank the sample in the database based on the dissimilarity. It is computationally intensive to compute the dissimilarity of a query point in large databases, so we use TPH with EMR. Next step is to use rank to create Pareto points, based on the dissimilarity between the sample and query. The Pareto front is computed. First, Pareto front is set of non-dominated points called as the skyline. Second is found by removing the first Pareto front. The middle of Pareto front is defined as the median of a set of points.

High dimensional search is the problem in many CBIR systems and it is also used in many applications such as information retrieval, data mining, and computer vision. There is a most basic problem in nearest neighborhood search. It is difficult when the dataset contains the number of data points.

To solve this problem number of methods was developed such as KD- tree [2] and locality sensitive hashing [3]. For the Nearest neighbor search (ANN) the binary hashing method has become popular due to excellent search and storage

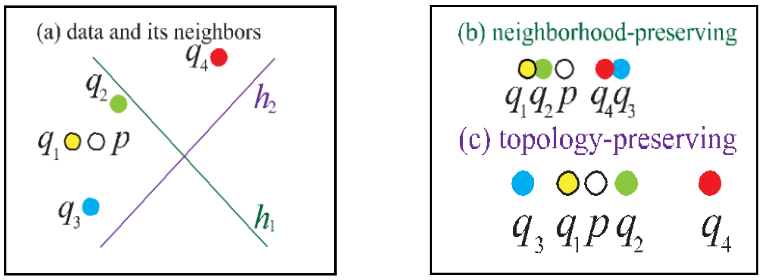

Fig 1,2. (a)Data point p and its neighbor (b) Neighborhood relation is reserved but ranking is lost (c) Beside the neighborhood relation, ranking is also preserved.

Binary hashing method maps the data y to a binary code H(y) and performs a bit-wise operation. The Dataset lies on the low dimensional manifold surrounded in high dimensional space [4]. For preserving the neighborhood relationship lot of method was developed. In this method hasa lot of neighborhood relation are taken into account with the learning process e.g. ranking is not. This method cannot preserve the data topology.

As shown in fig. 1(b), for a data point p and its neighbors q1, q2, q3,q4, the hamming embedding 's{h_1 (q_i) }_(i=1)^4 are still the neighbor of h1(p). The neighbor ranking is not taken, the ranking between neighbors of p is maintained. To maintain the topology of a data set, a known way is the original distance is maintained. In these methods for reconstruction of the distance between datapoints in the original data space, the hamming distance between the binary codes is used. The Hamming distance is discontinuous and surrounded by the code length, the original distance to Hamming distance mapping is many-to-one, which indicates then on-optimality of there constructions. Another drawback of most hashing methods is an inadequacy inproviding a good ranking. As most hashing methods simply accept Hamming distance as similarity metric in a search process, there are a lot of results that share the same distance to a query image, e.g. kNN search, Weighted Hamming distance[5],[6]-[7] have been developed to solve this limitation. If the ranking in form at ion is encoded in the codes, this limitation can be better eased.

In this paper, we propose a Topology Preserving Hashing (TPH) [20]method to solve the above two problems. Topology Preserving Hashing is to not only keep the neighborhood relationships but also keep the neighborhood rankings.As shown in Fig.1(c) :TPH ensures that h2(q1) and h2(q2) are neighbors of h2 (p), and h2(q1) is still a nearer neighbor of h2(p) in Hamming space. The main donation of this paper is briefly outlined as follows:

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We proposed a novel hashing method to learn

Hamming embedding's a data set such that it not only the neighborhood relationship but also the neighborhood ranking of each data point is preserved.

2. These mantic label information can be easily leveraged in the learning process of our method, extending it to a semi-supervised method to capture semantic neighbors.

3. Experimental results show the Excellences of our method as compared with other methods such as unsupervised and semi-supervised methods. The drawback of hashing method is a lack in proving the good ranking result.

II. RELATED WORK

The large scale specific object image retrieval systems are to find images that contain the query object in the image database. For example media, production teams are interested in searching images or video footage to accompany news reports and newspaper articles from the database. Obtain multiple images of the queried object using Google image search. Show that multiple queries significantly improve the system to find challenging occurrences of the queried object. The aim is to retrieve all images containing a specific object in an image dataset. This is a problem that has seen much progress and success over the last decade, the starting point for the search has been a single query image of the specific object of interest. In this work two changes to the standard approach: first, starting point the object is text, as they are interested in probing data sets to find known objects; and second the dataset using multiple image queries and combine the results into a single ranked list. Addressing this problem has been one of the main research themes in specific object retrieval research with developments in feature encoding to alleviate vector quantization (VQ) losses, and in augmentation of the bag of visual word (BOW) representation to alleviate detector and descriptor drop out (as well as, again, VQ losses).All time the conversion of textual is not possible for all the images.

Therefore, tree-based indexes are not desirable for high-dimensional search problems. Another kind of ANN search algorithm is based on the vector quantization, such as k-means LSH [8] and Product Quantization (AB) [9].In AB, by dividing each data into several sub spaces and expressing data in terms of recurring parts, the representational capacity of AB, grows aggressive in the number of sub spaces. In these methods, each data point is represented by a feature vector and the search process is performed. As a result, the search process is time-consuming. Recently, the hashing based method has been widely used for similarity search and similar applications as it allows the constant-time search. A lot of hashing methods have been proposed these can be divided into two main categories : data-independent methods [3], [10] and data-dependent methods. Theoretically, it is guaranteed that the original distances are asymptotically saved in the Hamming space within creasing code length; hence, LSH related methods usually require long codes to achieve good accuracy. However, long codes result in the collision probability of similar points mapped to close codes decreases as the code length increases. As a result, the LSH- related methods usually construct multi-tables to ensure a reasonable probability that a query will collide with its near neighbors in atleast one table, which leads to long query time and increases the memory occupation. Recently, many data-dependent

methods, which focus on learning hash functions from the data set, have been developed to learn more compact codes.

The neighborhood relationships between sub-regions and the relative proximities between neighbors of each sub-region are both essential [11] for effective dimension reduction. Many hashing methods have been developed for neighborhood-preserving [4] or distance-preserving [12]. The former one sign or the neighborhood rankings, and latter to support and a manifold with rigid steel beam [11] while in many cases, the optimal embedding of a manifold needs some flexibility: somesub- regions should be locally stretched or shrunk to embed the min to alow-dimensional space where the topology can be well preserved. Therefore, these hashing methods cannot preserve the data set topology well.

In manifold learning area, it is true that a manifold can be entirely characterized by giving the relative or comparative proximities [11], e.g.a first region is close to a second one but far from a third one. Comparative in formation between distances, like in equalities or rankings, suffices to characterize a manifold for any embedding's. Moreover, for many similarity search problems, the relative rankings of results are more important than their actual similarities to a query. Based on the above introduction, we can conclude that more effective Hamming embedding's can be learned by incorporating the data set topology with the learning process. Further more, if the local topology is well preserved in Hamming space, the ambiguity caused by ranking with Hamming distance can be better all eviated.

There is wide use of Pareto-optimality [1] in the machine learning community. Complex multi-objective optimization problems are solved by this method, where finding the first Pareto front is challenging. Several efficient algorithms have been developed for finding the Skyline method. In our PFM algorithm, Efficient and fast Skyline algorithms or fast non-dominated sorting can be used to find each Pareto front.

III. PROPOSED METHOD

A. Feature extraction:

Texture feature- we will briefly describe the four methods used for texture feature extraction:
(1) Gabor filters, (2) wavelet transform and (3) HOG based methods.

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Gabor filter- A Gabor filters [13] bank is composed of a set of Gaussian filters that wrap the frequency domain with different radial frequencies and orientations. Gabor filter defines low dimensional features the total frequency is nf. Total orientation is no.

The 2D Gabor wavelet is defined as follows:

$$H(x, y, \theta, \sigma)=\frac{1}{2\pi\sigma^2} exp\left\{-\frac{x^2+y^2}{2\sigma^2}\right\} exp\{2\pi j(ux\cos\theta + \quad uy\sin\theta)\} \tag{1}$$

where uis the frequency of a sinusoidal wave, θ adjusts the orientation of the wave, σ is a standard deviation of Gaussian function in x and y-direction and j=√(-1).The output of the Gabor filter can be given as a 2D convolution of the input images of I(x,y) and G (x,y) for particular u, θ and σ. For the purpose of simplicity, we assume that the Gaussian curve is symmetrical. Where, the filter bank was created with 6 orientations (0º, 30º, 60º, 90º, 120º and 150º).

Wavelet transform- This transform provides a robust method for texture analysis. The wavelet transform allows for the decomposition of signal using a series of elemental function called as wavelet and scaling, which are created by scaling and translation of a base function, known as the mother wavelet:

$$\psi\_(s,u)=1/\sqrt{s}\ \psi((x-u)/s) \tag{2}$$

S governs the scaling, u the translation.

Wavelet is applied as the high pass filter while scaling is equal to low pass filter.

Histogram of oriented gradient-It[14] is widely used for face and human detection. For each pixel edge, gradients and orientations are calculated. The edge gradients and orientations are obtained by the Sobel filters. The gradient magnitude is m(x, y) and orientation is θ(x, y) are calculated using the x and y directional gradients of dx(x, y) and Dy(x, y) computed by Sobel filter as,

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$$M(x,y) = \sqrt{dx(x,y)^2 + dy(x,y)^2} \tag{3}$$

$$\Theta(x, y) = \begin{cases} \tan-1\left(\frac{\mathrm{dy(x,y)}}{\mathrm{dx(x,y)}}\right) - \pi & \text{if } \mathrm{dx(x,y)} < 0 \; and dy(x,y) < 0 \\ \tan-1\,(\mathrm{dy(x,y)/dx(x,y)} \; + \pi & \text{if } \mathrm{dx(x,y)} < 0 \;\; 0 \; and dy(x,y) > 0 \\ \tan-1(\mathrm{dy(x,y)/dx(x,y)}) & \text{otherwise} \end{cases} \tag{4}$$

Dividing the local region into a small local area known as" cell". Cell size is a 4x4 pixel. 8 bin gradient orientations are calculated. Where h (k) k=0 to 7.

Color feature –We will briefly describe the two methods used for feature extraction: (1) auto-correlogram, (2) color moment. It is used to describe the effectiveness and efficiency of the color feature. The Color is a widely used important feature for image representation. Color space; color quantification and similarity measurement are the key components of color feature extraction.

Auto-correlogram- This method [15] use the HSV to improve the performance. To find the spatial relation of the color, where [C] is the set of colors c_1 c_2…c_n. [D] Is fixed distance of$d_1 d_2$…..$d_n$which is measured using $L_{2\ norm}$.I(P) denote the color c,

$$h_{c_i}(I) = p_r \;\; [p \in Ic_i \;] \tag{5}$$

$$\gamma_{c_i c_j}^{(d)} \equiv pr_{p1 \in I_{c_1}, p_2 \in I} \left[P_2 \in I_{c_j} \,|\, |P_1 - P_2| = d \right] \tag{6}$$

The difference between the query Q and database B are measured using weighted Euclidean distance in a case of auto-correlogram.

$$D_h(Q,R0) = [h(Q) - h(R)]^t \, A[h(Q) - h(R)] \tag{7}$$

$$D_\alpha(Q,R) = \textstyle\sum_{c \in [c], d \in [D]} |\alpha_c^{(d)} - \alpha_c^{(d)}(R) \tag{8}$$

Weighted matrix a, a_{ij} correspond to the similarity of color c_i and c_j, H (Q) the histogram of the image Q with the quantized set of color[C].

Color moment- color moment [16] is known by the mean, variance, standard deviation. 1^{st} order and 2^{nd} order is calculated 10x10 regions around the interest points for the RGB channel.

$$\text{Mean} = \textstyle\sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} / nm \tag{9}$$

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Variance= $\frac{1}{nm}\sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij}-mean)^2$ (10)

Standard deviation= $\sqrt{varience}$ (11)

X_{ij} is the pixel value of i^{th} row and j^{th} column.

B. Pareto points – Pareto optimality [1] is applied in many fields because it is a powerful concept. A more robust approach involves finding the Pareto optimal solution. A feasible solution $x\epsilon s$ is Pareto optimal no other feasible solution ranks better in every objective. X strictly dominate Y, $f_i(x) < f_i(y)$for all I and $f_j(x) < f_j(y)$ for some j.$x \in s$ is Pareto optimal if it is not strictly dominate. Set of the Pareto-optimal feasible solution is called as the first Pareto front. First, Pareto front consist of the set of the non- dominated points, called as the skyline [8-9]. First, Pareto front is denoted as F1.Second Pareto front is denoted as F2 is obtained by removing first Pareto front and for remaining data Pareto front is found

F_i = Pareto front of the set$\frac{s}{(\cup_{j=1}^{i-1}F_j}$ (12)

1) Information retrieval using Pareto front method- data set $X_m=\{X_{1....}\ X_N\}$ where query image is compared with the database image. When it is a multiple queries then issue each image and then combine their results into one partially ordered list. $T > 1$ Denotes T-tuple of queries by $\{q_1, q2.... q_n\}$ and dissimilarity points query q and i & jth terms in the database. Each Pareto points p_j corresponding to a sample x_j from the database x_m. Denote all Pareto points by p. Where the Pareto points p_i dominates another point's p_j if d$l(i) \leq dl(j)$where p_i dominate p_j, x_i is closer to every queryx_j. Idea is to return the samples to which Pareto front it lies. Return f1, then f2 and so on until the sufficient images are retrieved.

C. EMR-EMR problem shown in[17]. $X = \{X_1, X_2 \ldots\ldots X_n \subset R^m$ Be the finite set of points $d: X \times X \to R$ be matrix on X, such as Euclidean distance. Vector Y= $\{Y_1, Y_2 \ldots Y_n\}$ where y_i=1 for x_i is the query and y_i=0 otherwise.

Let $r: X \to R$ denotes the ranking. Based on the distance the image is ranked. Based on the distance the image is ranked. Where query image is ranked as 1 all other image are given small ranks. The Graph is constructed on X, first find the distance between the samples in the ascending order, add edges between the points according to order until connected graph G is constructed. Edge weight x_i andx_j on the graph is denoted by wij.$wij = exp[-d2(Xi, X j)/2\sigma 2]$if not, set $wi\,j$ = 0, and set$W = (W_{ij})ij\epsilon Rn \times n$.The manifold ranking method, cost function is denoted by,

$O(r) = \sum_{i,j=1}^{n} wij\ |1/\sqrt{D_{ii}} \times r_i - 1/\sqrt{D_{jj}} \times r_j|^2 + \mu \sum_{i=1}^{n} |r_i - y_i|^2$ (13)

Where D is the diagonal matrix

$D_{ii} = \sum_{j=1}^{n} wij$ And $\mu < 0$. Cost function has two terms; the 1st term is the smoothness term. 2nd term is regularization terms.

The 1st term forces the nearby points have the similar ranking. The Second term forces the query to have rank close to 1 while the other samples are close to 0 as possible.

The iterative approach is suited. The direct approach requires NxN matrix and iterative requires NxN memory.

The final ranking function r can be directly computed by

$$r^* = (I_n - H^T(HH^T - \frac{1}{\alpha} \times I_d)^{-1}H)\, y \quad (14)$$

Where $H = ZD - \frac{1}{2}$ and D is a diagonal matrix with$D_{ii} = \sum_{j=1}^{n} z_i^T z_j$ this method requires inverting only a $d \times d$ matrix. The complexity of computing the ranking functions with the EMR algorithm is$O(dn + d3)$.

D. Topology preserving hashing- We begin with the definition of *local topology preserving* [18]: For datapoints $x1, x2, x3, x4$ and their embedding's $\{y_i = \varphi(x_i)\}_{i=1}^{4}$. The embedding $\varphi: x \rightarrow y$ is called local topology preserving following condition:

If $d(x_1, x_2) \leq d(x_3, x_4)$, then $\tilde{d}(y_1, y_2) \leq \tilde{d}(y_3, d_4)$d and$\tilde{d}$ is distance matrix in original and embedded data space.

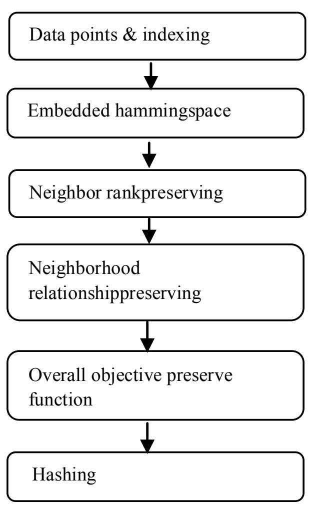

Fig 3. Topology preserving hashing method

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1) Neighborhood ranking preserving [19]:

We define new "neighbor" set as the topo-neighbor

Set and denote it by$N_i \subset \mathcal{X}$, we add several data points which are not neighbor to the original data points.

Where the d_{ij} to denote $d_m(x_i, x_j)$ and h_{ij} to denote$d_H(y_i, y_j)$,

Where R(y) becomes,

$$R_y = \frac{1}{2} \sum_i \sum_{j_1 j_2} (d_{ij_1} - d_{ij_2})(h_{ij_1} - h_{ij_2}) \quad (15)$$

We define neighborhood distance difference matrix $D_i \epsilon \mathbb{R}^{n_i \times n_i}$.

Where hamming distance h_{ij}can be expressed as,

$$h_{ij} = \frac{m - \sum_{k=1}^{m} y_k^{(i)} y_k^{(j)}}{2} \quad (16)$$

Where R(y) can be rewritten as,

$$R(y) = \sum_k \sum_i \sum_{j_2} y_k^{(i)} c_{ij_2} y_k^{(j2)} - \sum_k \sum_i \sum_{j_1} y_k^{(i)} (-c_{ij_1}) y_k^{(j1)} \quad (17)$$

$$= 2 \sum_k \sum_i \sum_j y_k^{(i)} c_{ij} y_k^{(j)} \quad (18)$$

Equation (18) can be expressed in a compact matrix for by showing a weight matrix$\Gamma_r \epsilon \mathbb{R}^{n \times n}$. Calculate$c_{ij}$ for x_i

$$c_{ij} = \begin{cases} \sum_{x_s \in N_i} (d_{is} - d_{ij}) & : x_j \in N_i \\ 0 & : otherwise \end{cases} \quad (19)$$

After removing the constant coefficient (18) can represent as,

$$R(y) = Tr\{y \Gamma_r y^T \quad (20)$$

Where Γ_r is called as the rank- weighting matrix. We call rank weight where it indicates the relative ranking between the neighbors of data point's x_i.

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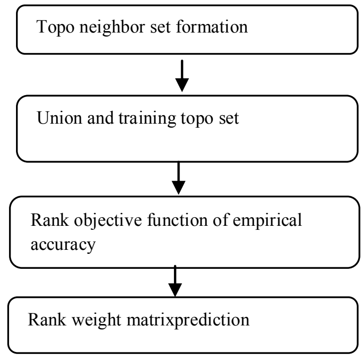


Fig 4. Neighborhood ranking preserving

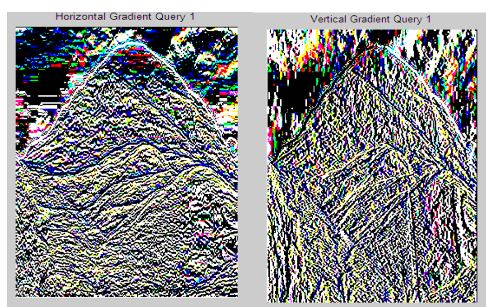
2) Neighborhood relation preserving: R(y) is to preserve the neighborhood ranking for each data points.Where w_{ij} is the similarity between x_i, xj in the original database w_{ij}=exp $\{-\frac{-d_{ij}{}^2}{\sigma_s^2}\}$Where σ_s is the pairwise distance.

$$S(Y) = -Tr\{y\Gamma_s y^T\} \tag{21}$$

Linear hashing functions: Optimal hamming embedding Y that preserves the original neighborhood topology. Where y cannot be generalized to a new data directly. Where encoding process can be expressed as

$$Y = sgn(W^T X) \tag{22}$$

IV. EXPERIMENTAL RESULTS



(a) (b)

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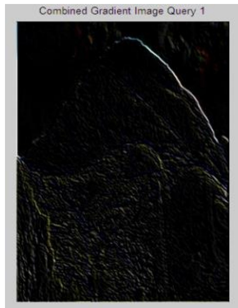
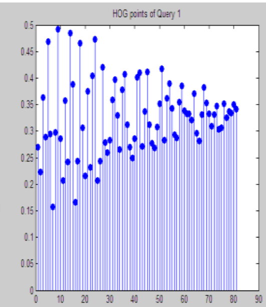
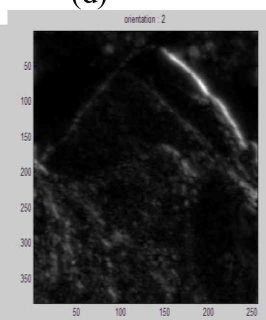


(c)

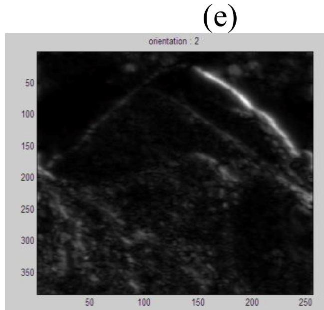


(d)

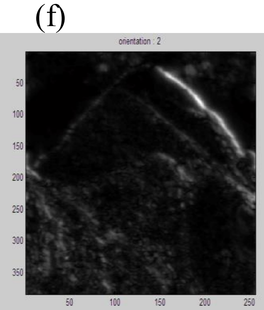
(e)



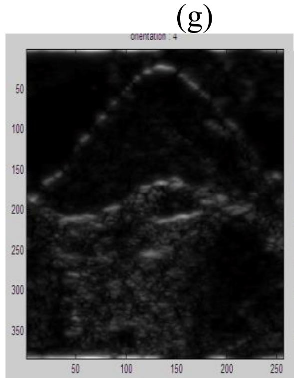
(f)



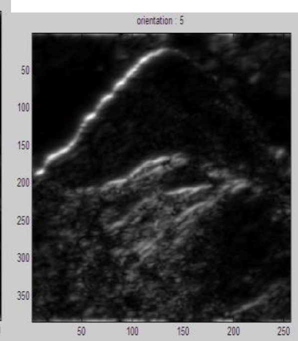
(g)



(h)



(i)



(j)

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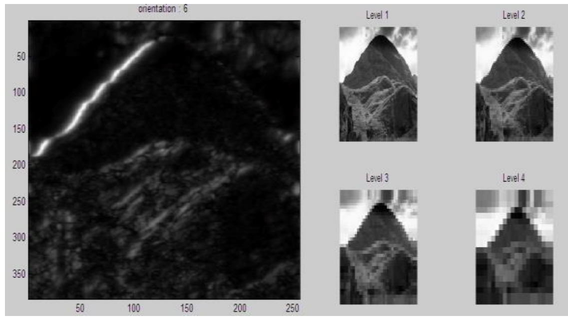
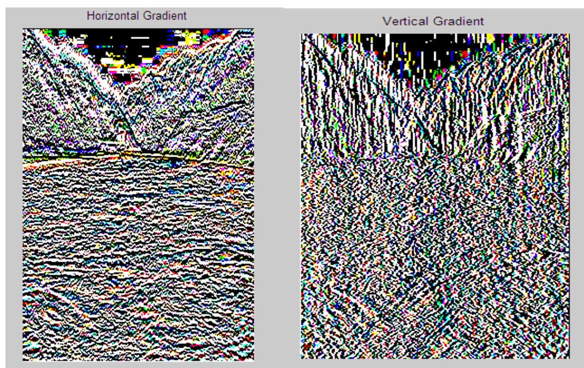
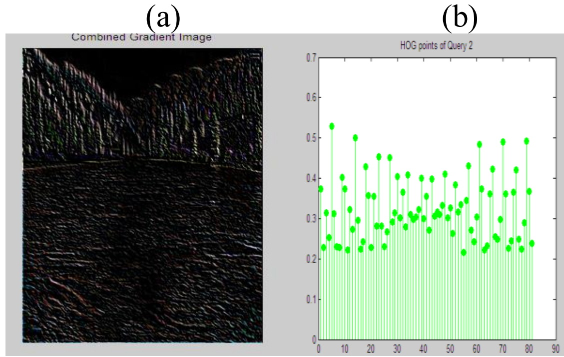


(k) (l)

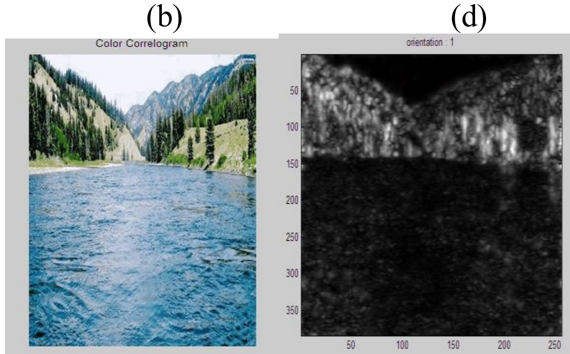
Fig 5. Query 1 (a) vertical gradient (b) horizontal gradient(C) combined gradient (d) HOG points (e) color correlogram (f)-(k) orientation (l) wavelet level.



(a) (b)



(b) (d)



(e) (f)

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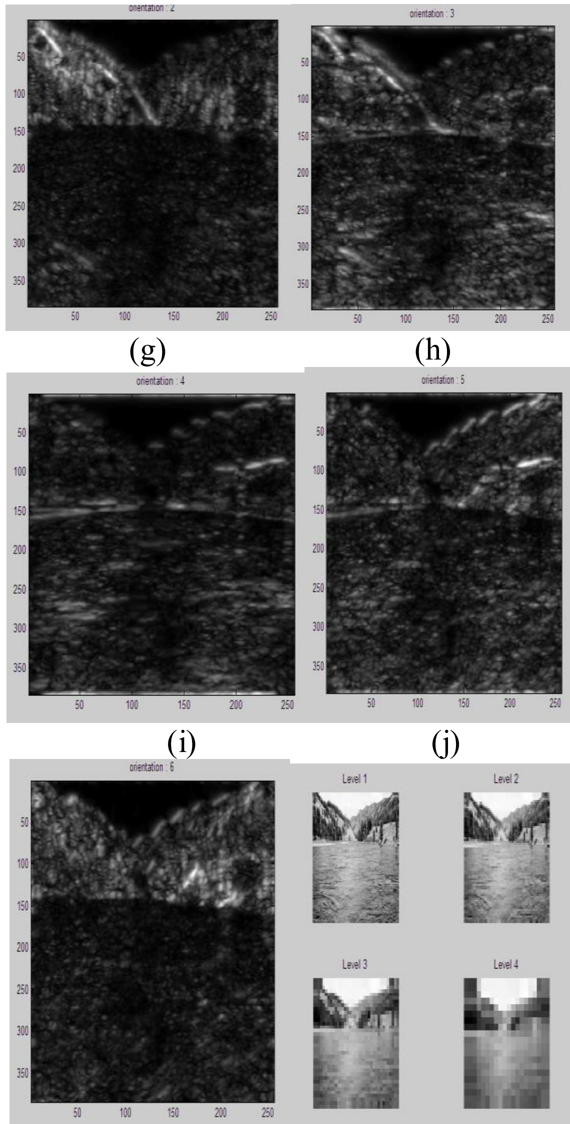

(g) (h) (i) (j) (k) (l)

Fig 6. Query 2 (a) vertical gradient (b) horizontal gradient(C) combined gradient (d) HOG points (e) color correlogram (f)-(k) orientation (l) wavelet level.

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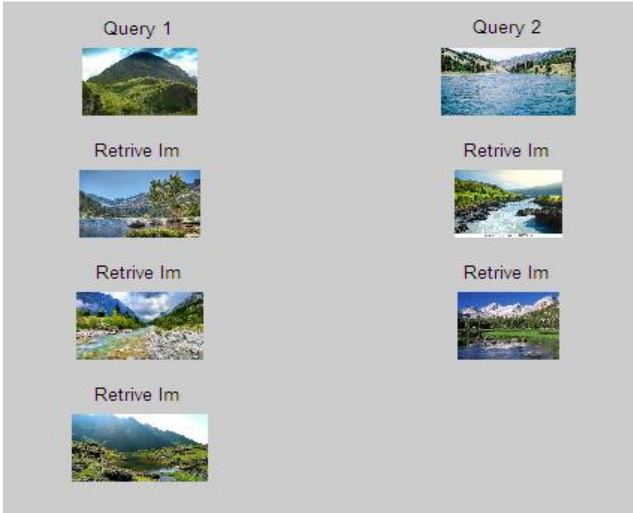

Fig 7 Output image

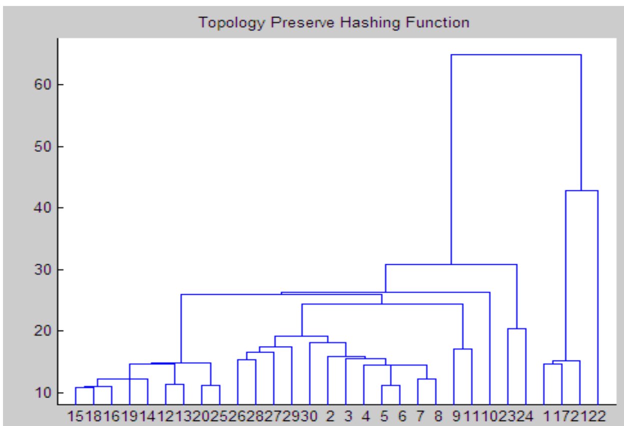

Fig 8 topology preserving hashing function

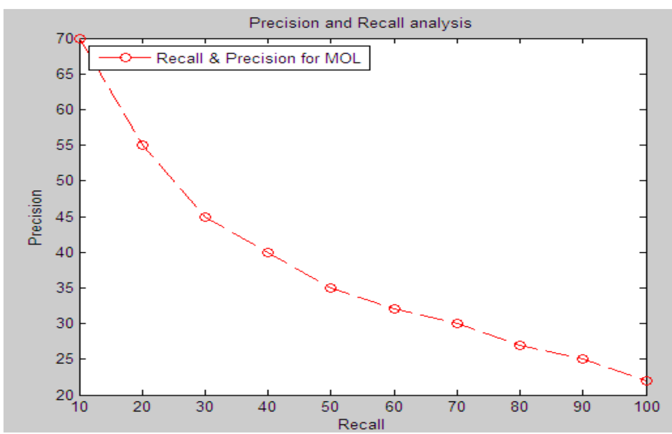

Fig 9 precision and recall analysis

Fig 9 gives the precision recall curve. The map values of all method of different code length it is easy to find out that the TPH outcome and the other state of art binary hashing methods.

IV. CONCLUSION

We have presented the algorithm for the CBIR. Our aim is to find the related image to the given queries. EMR is used for ranking which is a very fast method. To add advantage the Pareto front method and TPH is used. The Theoretical result on asymptotic non-convexity of Pareto fronts proves that Pareto front is better than the linear ranking method. To obtain meaningful neighbor many hashing method was developed to preserve the neighbor relation but ignore the neighbor ranking. In this paper we have shown that the ranking is more important than neighborhood relation for learning the hashing. In proposed method Topology preserving hashing used the neighborhood relationship between the data points, but also the neighborhood rankings.

REFERENCE

[1] ko-jen Hsiao, jeff calder " paerto- depth for multiple-query image retrieval" IEEE trans on image processing vol. 24 pp. 583-594, feb 2015

[2] J. L. Bentley and B. Labo, "K-d trees for semi dynamic point sets," in Proc. 6th SOCG, 1990, pp. 187–197.

[3] A. Andoni and P. Indyk, "Near-optimal hashing algorithms forapproximate nearest neighbor in high dimensions," in Proc. 47th Annu. IEEE Symp. FOCS, Oct. 2006, pp. 459–468.

[4] W. Liu, J. Wang, S. Kumar, and S.-F. Chang, "Hashing with graphs," in Proc. 28th ICML, 2011, pp. 1–8.

[5] M. Jain, H. Jégou, and P. Gros, "Asymmetric hamming embedding: Taking the best of our bits for large scale image search," in Proc. 19thACM Int. Conf. Multimedia, 2011, pp. 1441–1444.

[6] Y.-G. Jiang, J. Wang, X. Xue, and S.-F. Chang, "Query-adaptive image search with hash codes," IEEE Trans. Multimedia, vol. 15, no. 2, pp. 442–453, Feb. 2013.

[7] L. Zhang, Y. Zhang, J. Tang, K. Lu, and Q. Tian, "Binary coderanking with weighted hamming distance," in Proc. IEEE Conf. CVPR, Jun. 2013, pp. 1586–1593.

[8] L. Paulevé, H. Jégou, and L. Amsaleg, "Locality sensitive hashing: A comparison of hash function types and querying mechanisms," PatternRecognition. Lett., vol. 31, no. 11, pp. 1348–1358, Aug. 2010.

[9] H. Jegou, M. Douze, and C. Schmid, "Product quantization for nearest neighbor search," IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 1, pp. 117–128, Jan. 2011.

[10] J. Ji, J. Li, S. Yan, B. Zhang, and Q. Tian, "Super-bit locality-sensitive hashing," in Proc. NIPS, 2012, pp. 108–116.

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Vol. 2, Issue 8, August 2016

[11] J. Lee and M. Verleysen, Nonlinear Dimensionality Reduction.New York, NY, USA: Springer-Verlag, 2007.

[12] Kulis and T. Darrell, “Learning to hash with binary reconstructive embedding’s,” in Proc. 23rd Annu. Conf. NIPS, Jul. 2009, pp. 1042–1050.

[13] Weitao Li, KeZhi Mao, Hong Zhang, andTianyou Cha “selection of Gabor filters for improved texture feature extraction” IEEE Trans. On image processing,PP.361-364,sept 2010[17th international conference]

[14] K.velmurugan, dr.s.santhosh baboo “ image retrieval using Harris corners and histogram of oriented gradients” international journal of computer applications, vol 2-no.7, PP 6-10,june 2011

[15] AMIT SINGLE,MEENAKSHI GARG “ CBIR approach based on combined HSV, auto correlogram, color moments and Gabor Wavelet” international conference, vol3, PP 9007-9012, Oct2014.

[16] S.R. Kodituwakku et al “comparison of color features for image retrieval” Indian journal of computer science and engineering, vo.1, PP 207-211

[17] D. Zhou, J. Weston, A. Gretton, O. Bousquet, and B. Schölkopf, “Ranking on data manifolds,” in Advances in Neural Information Processing Systems, vol. 16. Cambridge, MA, USA:MIT Press,2004,pp.169–176

[18] D. Luo, C. H. Ding, F. Nie, and H. Huang, “Cauchy graph embedding, “inProc. 28th ICML, 2011, pp. 553–560

[19] L. Zhang, Y. Zhang, J. Tang, X. Gu, J. Li, and Q. Tian, “Topology preserving hashing for similarity search,” in Proc. 21st ACM Int. Conf. Multimedia, 2013, pp. 123–132.

[20] L. Zhang, Y. Zhang, J. Tang, X. Gu, J. Li, and Q. Tian, “scalable similarity search with topology preserving hashing” in IEEE trans on image processing, vol. 23, July 2014, pp. 3025-3039.