Middle-East Journal of Scientific Research 24 (S2): 127-131, 2016
ISSN 1990-9233

DOI: 10.5829/idosi.mejsr.2016.24.S2.130

Multiple-Query Image Retrieval Based on Pareto Front Method with Em-Ranking

M. Padmaa and T. Noorul Binoona

Department of ECE, Saranathan College of Engineering, Trichy, India

Abstract: Content-based image retrieval (CBIR) uses either one single query, or multiple queries include same semantic information or same object. In this paper, we consider multiple query images corresponding to different image semantics. Recent research shows these features are not associated with query-by-one (QBO) which is insufficient to achieve good performance. Thus, query-by-multiple (QBM) methods are introduced and applied in many content-based image retrieval systems. In this method, multiple query image retrieval uses Pareto front method (PFM) with EMR. Feature extraction by HOG method is used to decrease the complexity.

Key words: Pareto fronts · EM ranking · Multiple query retrieval · Content-based image retrieval · HOG

INTRODUCTION

In Text-based image retrieval, traditional database techniques are used for retrieving the image. Through text descriptions, images can be organized by semantic hierarchies to facilitate easy browsing based on standard Boolean queries. Although, text-based methods are reliable and speed when images are annotated, they are incapable of searching in unannotated image collections. The information retrieval from the text domain to the image database is, however non-trivial. Recently, content- based image retrieval has become popular for the retrieval of the image. CBIR has become important problem in information retrieval in past two decades [1-2]. Several multiple image retrieval is proposed in literatures [3].

The image includes both the visual and semantic contents. Visual content defines the low-level features of the image includes color, texture etc., Semantic contents are obtained by texture annotation. Content- based image retrieval technique which uses visual contents to search images from databases according to users' interests. The similarity between the feature vector of Query images and images in the database are used for retrieval process. In this paper, multiple queries are taken as the source image. The first step is to rank all samples in the database based on the dissimilarities to the query image. HOG and Gabor filter method are used to compute the dissimilarities. Next step is to find the Pareto points based on dissimilarities between samples. Set of Pareto point is called the Pareto front. Middle of Pareto front is called as the median of the points. From Fig 1 shows the Pareto front for query images corresponding to the forest and the river. Images (1, 2 and 3) contain the features of the query1. Images (7, 8 and 9) contain the features of the query image2. Middle part contains the features of both the images. Hence, it is desirable for the multiple query image retrieval.

Related Work: The algorithm consists of the following steps as shown in Figure 2.

Feature Extraction: The main function of the CBIR system is feature extraction. Feature extraction captures the certain properties of the image. The Global features for the entire image and local features for the region. A global feature like color, shape etc, local features like texture. From the extracted features the feature vector is formed. The feature vector is stored for the future use. The feature vector is used to search the similarity between the query image and the database.

Texture Feature: The image can be modeled into two dimensions for the texture identification. Many techniques has been used for measuring the texture features such as Co-Occurrence matrix, Gabor filter, HOG, wavelet transform.

Corresponding Auhor: M. Padmaa, Associate Professor, Dept of ECE, Saranathan College of Engineering, Trichy, India.

Fig. 1: Pareto front method where image in middle contains the semantic information of the both the images

Gabor Filter: Gabor Filter is a group of wavelets capturing energy at a specific frequency and at specific direction. Gabor filter [4] defines the parameter such as the frequency, orientation and smoothness. It reduces the computational complexity of texture feature. Gabor filter defines low dimensional features the total frequency is n_f. Total orientation is n_o. Gabor filter employs a bank of band-pass filter followed by the energy filter.

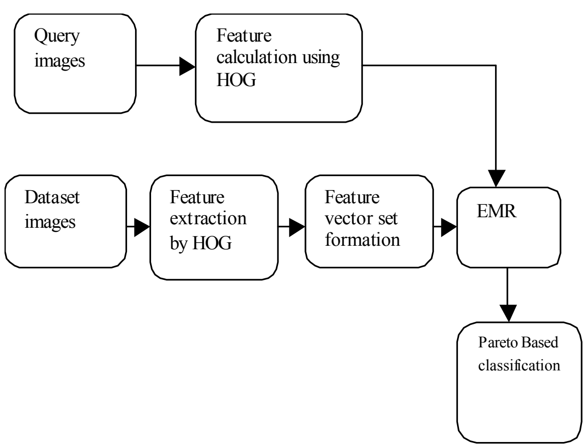

Fig. 2: Block diagram for the proposed system

The 2D Gabor wavelet is defined as follows:

$G(x, y, \theta, \sigma) =$

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

where u is the frequency of sinusoidal wave, θ adjusts the orientation of the wave, σ is a standard deviation of Gaussian function in x and y direction and $j = \sqrt{-1}$. The output of the Gabor filtering 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.

Histogram of Orientation Gradient: HOG [5] method is used for feature extraction. It 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,

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

$\Theta(x, y) =$

$$\begin{cases} \tan - 1\left(\dfrac{dy(x,y)}{dx(x,y)}\right) - \pi \\ \quad \text{if } dx(x,y) < 0 \text{ and } dy(x,y) < 0 \\ \tan - 1\,(dy(x,y)/dx(x,y)) + \pi \\ \quad \text{if } dx(x,y) < 0 \;\; 0 \text{ and } dy(x,y) > 0 \\ \tan - 1(dy(x,y)/dx(x,y)) \\ \quad \text{otherwise} \end{cases} \tag{3}$$

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: Color is the important feature of the image representation. RGB, HSV color model is used for the work. To evaluate the effectiveness and efficiency of the color feature, the following descriptor is used. The similarity measure is the important key components of the color feature extraction.

Auto-Correlogram: This method [6] use the HSV instead of the RGB to improve the performance of the auto-correlogram. Detect the spatial relation of the color where [C] is the set of colors $c_1, c_2 \ldots c_n$. [D] Is fixed distance where $d_1, d_2 \ldots d_n$, which is measured using L_2 norm. I (P) denote the color c,

$$h_{c_i}(I) = p_r\ [p \in Ic_i\ ] \tag{4}$$

$$\gamma^{(d)}_{c_i c_j} \equiv pr_{p1 \in I_{c_1}, p2 \in I} \left[P_2 \in I_{c_j} \mid |P_1 - P_2| = d \right] \tag{5}$$

The difference between the query Q and database are measured using weighted Euclidean distance in a case of auto-correlogram; the dissimilarity is measured by the norm L1.

$$D_h(Q, R0) = [h(Q) - h(R)]^t A [h(Q) - h(R)] \tag{6}$$

$$D_\alpha(Q, R) = \sum_{c \in [c], d \in [D]} |\alpha_c^{(d)} - \alpha_c^{(d)}(R) \tag{7}$$

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 [7] is known by the mean, variance, standard deviation. 1st order and 2nd order is calculated 10x10 regions around the interest points for the RGB channel.

$$\text{Mean} = \sum_{i=1}^{n} \sum_{j=1}^{m} x_{ij} / nm \tag{8}$$

$$\text{Variance} = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} (x_{ij} - mean)^2 \tag{9}$$

$$\text{Standard deviation} = \sqrt{varience} \tag{10}$$

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

Pareto Points: Pareto optimality 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. $x \ \epsilon \ s$ is Pareto optimal if it is not strictly dominate by another item. 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

$$F_i = \text{Pareto front of the set } \frac{s}{(\cup_{j=1}^{i-1} F_j} \tag{11}$$

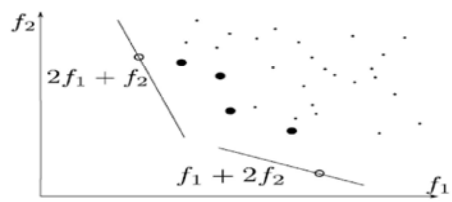

Fig. 3: Depiction of non convexities in the first Pareto front

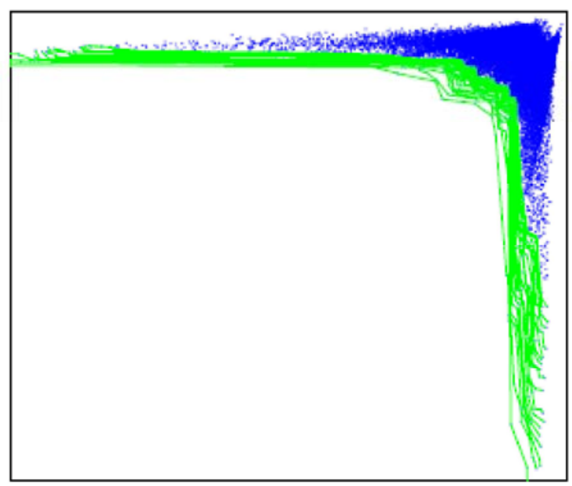

Fig. 4: Depiction of non convexities in the Pareto fronts in the real-world Media mill dataset

Fig 3 shows Pareto front method for ranking. Large point is Pareto optimal, hollow point can be obtained as the top ranking using linear scalarization. Fig4 show the Pareto Fronts Problem in the multiple query retrieval using real data from the scalarization.

Information retrieval using Pareto front method- data set $X_m = \{X_{1 \ldots} X_N\}$ 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 $\{q_1, q2 \ldots q_n\}$ 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 points p_j if d $l(i) \leq dl(j)$ where p_i dominate p_j, x_i is closer to every query x_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 [10]. $X = \{X_1, X_2, ..., X_n \subset R^m\}$ Be the finite set of points $d{:}X \times X \rightarrow R$ 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 $r{:}X \rightarrow R$ 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 and x_j on the graph is denoted by *wij*, $wij = exp[-d2(Xi, Xj)/2\sigma 2]$ if not, set $wi\,j = 0$ and set $W = (W_{ij})ij \in Rn$. The manifold ranking method, cost function is denoted by,

$$O(r) = \sum_{i,j=1}^{n} wij \; | \, 1/\sqrt{D_{ii}} \times r_i - 1/\sqrt{D_{jj}} \times r_j |^2 + \mu \sum_{i=1}^{n} |r_i - y_i|^2 \qquad (12)$$

where D is the diagonal matrix

$D_{ii} = \sum_{j=1}^{n} wij$ And $\mu < 0$. Cost function has two terms; the 1[st] term is the smoothness term. 2[nd] 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 optimization problem is solved by two ways: direct approach and iterative approach. Direct approach finds the exact solution. For the large datasets, 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

$$r^{\circ} = (I_n - H^T(HH^T - \tfrac{1}{\alpha} \times I_d)^{-1} H)y \qquad (13)$$

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 $O(dn + d3)$.

Experimental Results

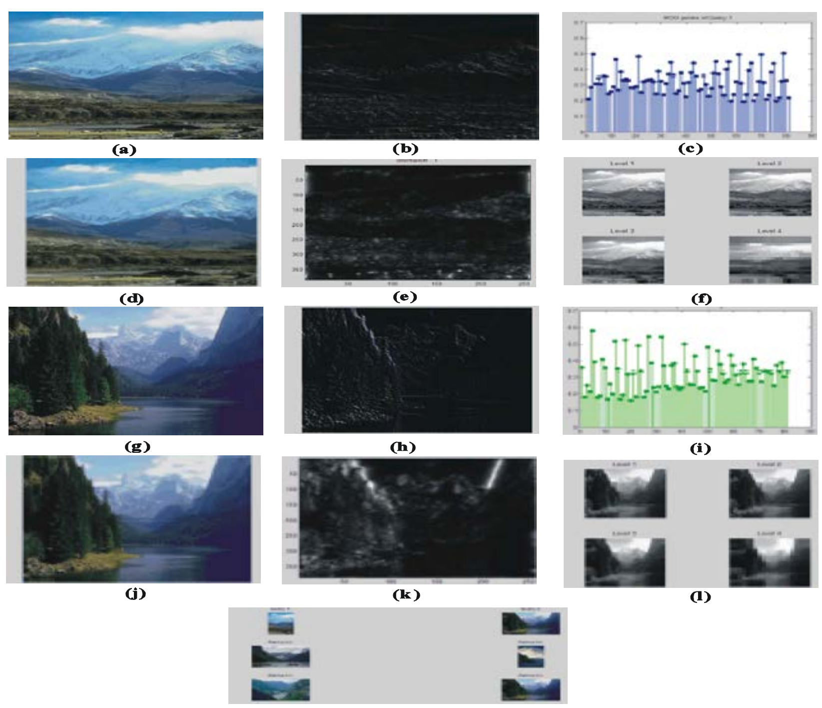

Fig. 5: Shows result (a) source image for query1 size 384x256 (b) combined gradient for query1 (c) HOG points for query1 (d) color correlogram for query1 (e) orientation for query1 (f) wavelet for query1 (g) source image for query2 (h) combined gradient for query2 (i) HOG points for query2 (j) color correlogram for query2 (k) orientation for query2 (l) wavelet for query2 (m) retrieved results

Performance Analysis: Performance analysis using normalized Discounted Cumulative Gain (nDCG), which measures the relevance of retrieved image. The Binary score is popular for the single image retrieval, 1 if retrieved image is close to query image, 0 otherwise. It does not work for a single image so define new performance assessment called multiple-query unique relevance (MQUR).Two query problem if the retrieved image is related to only single query features related to both the images.

The multiple query unique relevance (MQUR) of retrieved sample *X* having label *to* the query set by

$$\text{MQUR}(X) = \begin{cases} \frac{|l \wedge \beta|}{|\beta|}, & if \ \forall\ i, |l\ \wedge (yi - ni)i)| \neq 0, \\ 0, & \text{otherwise,} \end{cases} \quad (14)$$

MQUR_i for the Ith retrieved image. Discounted cumulative gain (DCG) for K- retrieved item is

$$\text{DCG}=\text{MQUR}_1 + \sum_{I=2}^{K} \frac{MQUR_I^1}{\log_2 I} \quad (15)$$

The normalized DCG, is computed by normalizing the DCG which is $1 + \sum_{I=2}^{k} \frac{MQUR_I^1}{\log_2 (I)}$

Table 1: nDCG value for different images

IMAGES	nDCG
Image 1	0.0111
Image2	0.0113
Image 3	0.0112

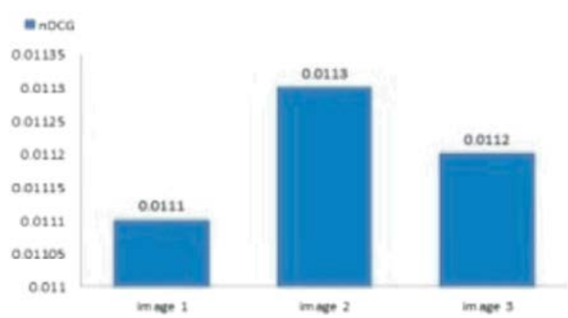

Fig. 6: nDCG graph for different images

CONCLUSION

We have presented the algorithm for the CBIR. Our goal is to find the related image to the given queries. This algorithm can easily retrieve the image where the other multiple query algorithms cannot easily retrieve. EMR is used for ranking which is a very fast method. Illustrate the advantage of Pareto front method. The Theoretical result on asymptotic non-convexity of Pareto fronts proves that Pareto front is better than the linear ranking method. Experimental studies illustrate the advantage of the proposed Pareto front method.

REFERENCES

1. Frome, A., Y. Singer and J. Malik, 2007. Image retrieval and classification using local distance functions, in Advances in Neural Information Processing Systems, vol. 19. Cambridge, MA, USA: MIT Press, pp: 417.
2. Gia, G. and F. Roli, 2004. Instance-based relevance feedback for image retrieval, in Advances in Neural Information Processing Systems. Cambridge, MA, USA: MIT Press, pp: 489-496.
3. Belkin, N.J., C. Cool, W.B. Croft and J.P. Callan, 1993. The effect multiple query representations on information retrieval system performance, in Proc. 16th Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retr., pp: 339-346.
4. Weitao Li, KeZhi Mao, Hong Zhang and Tianyou Cha, 2010. Selection of Gabor filters for improved texture feature extraction, IEEE trans. On image processing, pp: 361-364, sept 2010 [17th international conference].
5. Velmurugan, K., and Dr. S. Santhosh Baboo, 2011. image retrieval using Harris corners and histogram of oriented gradients, international Journal of Computer Applications, 2(7): 6-10.
6. Amit Single and Meenakshi Garg, 2014. CBIR approach based on combined HSV, auto correlogram, color moments and Gabor wavelet, International Conference, 3: 9007-9012.
7. Kodituwakku, S.R., *et al*, XXXX. Comparison of color features for image retrieval, Indian Journal of Computer Science and Engineering, 1: 207-211.
8. Borzsony, S., D. Kossmann and K. Stocker, 2001. The skyline operator, in Proc. 17th Int. Conf. Data Eng., pp: 421-430.
9. Kossmann, D., F. Ramsak and S. Rost, 2002. Shooting stars in the sky: An online algorithm for skyline queries, in Proc. 28th Int. Conf. Very Large Data Bases, pp: 275-286.
10. Zhou, D., J. Weston, A. Gretton, O. Bousquet and B. Schölkopf, 2004. Ranking on data manifolds, in Advances in Neural Information Processing Systems, vol. 16. Cambridge, MA, USA: MIT Press, 2004, pp: 169-176.