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An Adaptive Classification Algorithm of Pareto Method and Topology Preserve Hashing For Query-By-Multiple Image Retrieval System

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Abstract—Image Retrieval is a technique of searching, browsing, and retrieving the images from an image database. There are two types of different image retrieval techniques namely text based image retrieval and content based image retrieval techniques. Text-Based image retrieval uses traditional database techniques to manage images. Content-based image retrieval (CBIR) uses the visual features of an image such as color, shape, texture, and spatial layout to represent and index the image. This combination of features provides a robust feature set for image retrieval. Evaluate the performance of proposed methods at different precision value of the image retrieval on each category of image database. Recent research indicates that since these features are not exactly associated with image semantic meaning, query-by-one (QBO), which means to query with only one image, usually is insufficient to achieve good performance. Thus, query-by-multiple (QBM) methods are introduced and applied in many content-based image retrieval systems. However, how to maximize major features and minimize minor ones of these inputs while matching could influence retrieval results significantly. This technique is proposed novel multiple-query information retrieval algorithm that combines the Pareto front method with efficient Manifold ranking. Uniquely, to decrease the complexity of user input and reduce user-computer interaction, a topology preserve hashing algorithm will be introduced.

Keywords—Pareto Front Method(PFM),Histogram Of Gradient(HOG), Information Retrieval, Multiple query Retrieval, Efficient Manifold Ranking(EMR).

I. INTRODUCTION

In the past two decades content-based image retrieval (CBIR) has become an important problem in machine learning and information retrieval [1]–[3]. Several image retrieval systems for multiple queries have been proposed in the literature [4]–[13]. In most systems, each query image corresponds to the same image semantic concept, but may possibly have a different background, be shot from an alternative angle, or contain a different object in the same class. The idea is that by utilizing multiple queries of the same object, the performance of single query retrieval can be improved. We will call this type of multiple-query retrieval single semantic multiple query retrieval. Many of the techniques for single semantic multiple query retrieval involve combining the low level features from the query images to generate a single averaged query [14].

In this paper we consider the more challenging problem of finding images that are relevant to multiple queries that represent different image semantics. In this case, the goal is to find images containing relevant features from each and every query. Since the queries correspond to different semantics, desirable images will contain features from several distinct images, and will not necessarily be closely related to any individual query. This makes the problem fundamentally different from single query retrieval, and from single semantic multiple query retrieval. In this case, the query images will not have similar low level features, and forming an averaged query is not as useful. Since relevant images do not necessarily have features closely aligned with any particular query, many of the standard retrieval techniques are not useful in this context. For example, bag-of-words type approaches [18], which may seem natural for this problem, require the target image to be closely related to several of the queries. Another common technique is to input each query one at a time and average the resulting similarities. This tends to produce images closely related to one of the queries, but rarely related to all at once. Many other multiple query retrieval algorithms are designed specifically for the single-semantic-multiple-query problem[19] and again tend to find images related to only one, or a few, of the queries.

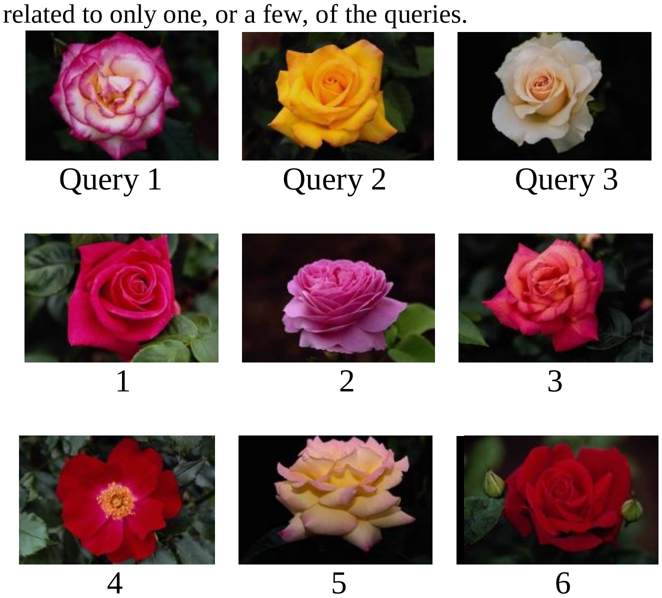

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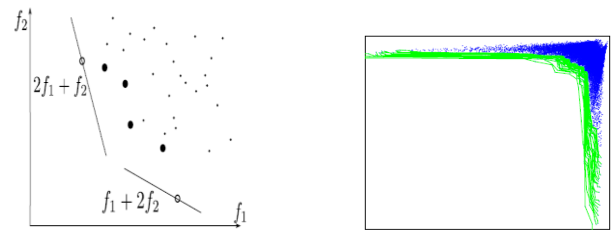
Fig.1. Images located on the first Pareto front when a multiple query images are issued. Images from the middle part of the front (images 10, 11 and 12) contain semantic information from both query images.

A key observation in this work is that the middle of the Pareto front is of fundamental importance for the multiple query retrieval problems. The middle of the Pareto front is defined as the median of the set of points on the front. Some work related to finding the middle of the Pareto front and useful properties of such Pareto points can be found in [15]. For three queries points on the Pareto front can be linearly ordered and the median is defined in the standard manner. For more than two queries a multidimensional generalization of the median, e.g., the mediod or the L1 median [10], [11], can be used to define the middle of the front. As an illustrative example, we show in Figure 1 the images from the first Pareto front for a multiple query images corresponding to a forest and a mountain. The images are listed according to their position within the front, from one tail to the other. The images located at the tails of the front are very close to one of the query images, and may not necessarily have any features in common with the other query. However, as seen in Figure 1, images in the middle of the front (e.g., images 10, 11 and 12) contain relevant features from both queries, and hence are very desirable for the multiple-query retrieval problem. It is exactly these types of images that our algorithm is designed to retrieve. The Pareto front method is well-known to have many advantages when the Pareto fronts are non-convex. In this paper, we present a new theorem that characterizes the asymptotic convexity (and lack thereof) of Pareto fronts as the size of the database becomes large.

This result is based on establishing a connection between Pareto fronts and chains in partially ordered finite set theory. The connection is as follows: a data point is on the Pareto front of depth n if and only if it admits a maximal chain of length n. This connection allows us to utilize results from the literature on the longest chain problem, which has a long history in probability and combinatory.

Our main result (Theorem 1) shows that the Pareto fronts are asymptotically convex when the dataset can be modeled as *i.i.d.* random variables drawn from a continuous separable log-concave density function $f : [0, 1]d \rightarrow (0,\infty)$. This theorem suggests that our proposed algorithm will be particularly useful when the underlying density is not log-concave. We give some numerical evidence (see Figure (2b)) indicating that the underlying density is typically not even quasi-concave. This helps to explain the performance improvement obtained by our proposed Pareto front method. We also note that our PFM algorithm could be applied to automatic image annotation of large databases. Here, the problem is to automatically assign keywords, classes or captioning to images in an unannotated or sparsely annotated database. Since images in the middle of first few Pareto fronts are relevant to all queries, one could issue different query combinations with known class labels or other metadata, and automatically annotate the images in the middle of the first few Pareto fronts with the metadata from the queries.



(a) (b)

Fig 2. (a)Depiction of nonconvexities in the first Pareto front.(b)Depiction of nonconvexities in the Pareto fronts in the real-world Mediamill dataset.

II. RELATED WORK

A. HISTOGRAM OF ORIENTED GRADIENT

The histogram of oriented gradient is a feature descriptor used in computer vision and image processing for the purpose of object detection. This technique counts occurrences of gradient orientation in localized portions of an image.

1) Gradient computation

The first step of calculation is the computation of the gradient values. The most common method is to apply the 1-D centered, point discrete derivative mask in one or both of the horizontal and vertical directions. Specifically, this method requires filtering the color or intensity data of the image with the following filter kernels:

$[-1, 0, 1]$ and $[-1, 0, 1]^T$

2) Orientation binning

The second step of calculation is creating the cell histograms. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. The cells themselves can either be rectangular or radial in shape, and the histogram channels are evenly spread over 0 to 180 degrees or 0 to 360 degrees, depending on whether the gradient is "unsigned" or "signed". Dalal and Triggs found that unsigned gradients used in conjunction with 9 histogram channels performed best in their human detection experiments.

3) Descriptor blocks

To account for changes in illumination and contrast, the gradient strengths must be locally normalized, which requires grouping the cells together into larger, spatially connected blocks. The HOG descriptor is then the vector of the components of the normalized cell histograms from all of the block regions. These blocks typically overlap, meaning that each cell contributes more than once to the final descriptor.

Two main block geometries exist: rectangular R-HOG blocks and circular C-HOG blocks. R-HOG blocks are generally square grids, represented by three parameters: the number of cells per block, the number of pixels per cell, and the number of channels per cell histogram.

Fig 4(a). Initial image

4) Block normalization

There are different methods for block normalization. Let υ be the non-normalized vector containing all histograms in a given block, $||\upsilon||_k$ be its *k*-norm for k=1,2 and e be some small constant (the exact value, hopefully, is unimportant). Then the normalization factor can be one of the following:

L2-norm:

$$f = \upsilon / \sqrt{||\upsilon||_2^2 + e^2}$$

L1-norm:

$$f = \upsilon / ||\upsilon||_1 + e)$$

L1-sqrt:

$$f = \sqrt{\upsilon} / (||\upsilon||_1 + e)$$

Fig 4(b). X derivative of initial image

Fig 4(c). Y derivative of initial image

Fig 4(d). Magnitude of Gradient

B. PARETO FRONT METHOD

Pareto optimality is a powerful concept that has been applied in many fields, including economics, computer

Science, and the social sciences [15]. We give her a brief

Overview of Pareto-optimality and define the notion of a Pareto front. In the general setting of a discrete multi-objective optimization problem, we have a finite set *S* of feasible solutions, and *T* criteria $f1, \ldots, fT : S \rightarrow$ R for evaluating the feasible solutions. One possible goal is to find $x \in S$ minimizing all criteria simultaneously. In most settings, this is an impossible task. Many approaches to the multi-objective optimization problem reduce to combining all *T* criteria into one. When this is done with a linear combination, it is usually called linear scalarization. Different choices of weights in the linear combination yield different minimizers. Without prior knowledge of the relative importance of each criterion, one must employ a grid search over all possible weights to identify a set of feasible solutions.

A more robust and principled approach involves finding the Pareto-optimal solutions. We say that a feasible solution $x \in S$ is *Pareto-optimal* if no other feasible solution ranks better in every objective. More precisely, we say that x strictly dominates y if fi (x) ≤ fi (y) for all i, and f j (x) < f j (y) for some *j* . An item $x \in S$ is Pareto-optimal if it is not strictly dominated by another item. The collection of Pareto-optimal feasible solutions is called the first Pareto front. It contains all solutions that can be found via linear scalarization, as well as other items that are missed by linear scalarization. The first Pareto front is denoted by *F*1. The second Pareto front, *F*2, is obtained by removing the first Pareto front from *S* and finding the Pareto front of the remaining data. More generally, the *i* th Pareto front is defined by

$$F_i = \text{Pareto front of the set } S \setminus \left(\bigcup_{j=1}^{i-1} F_j\right)$$

If $x \in Fk$ we say that *x* is at a *Pareto depth* of *k*. We say that a Pareto front *Fi* is deeper than Fj if i > j. The simple example in Figure 2(a) shows the advantage of using Pareto front methods for ranking. Here the number of criteria is *T* = 2 and the Pareto points [*f*1*(x)*, *f*2*(x)*], for

$x \in S$, are shown in Figure 2(a). In this figure the large points are Pareto-optimal, but only the hollow points can be obtained as top ranked items using linear scalarization. It is well-known, and easy to see in Figure 2(a), that linear scalarization can only obtain Pareto points on the boundary of the convex hull of the Pareto front. The same observation holds for deeper Pareto fronts. Figure 2(b) shows Pareto fronts for the multiple-query retrieval problem using real data from the Mediamill dataset. Notice the severe non-convexity in the shapes of the real Pareto fronts in Figure 2(b). This is a key observation, and is directly related to the fact that each query corresponds to a different image semantic, and so there are no images that are very closely related to both queries.

C. EFFICIENT MANIFOLD RANKING (EMR)

Let $X = \{X1, . . . , Xn\} \subset Rm$ be a finite set of points, and let $d : X \times X \rightarrow R$ be a metric on X, such as Euclidean distance. Define a vector $y = [y1, . . . , yn]$, in which $yi = 1$ if Xi is a query and $yi = 0$ otherwise. Let $r:X \rightarrow R$ denotes the ranking function which assigns a ranking score ri to each point Xi. The query is assigned a rank of 1 and all other samples are assigned smaller ranks based on their distance to the query along the manifold underlying the data. To construct a graph on X, first sort the pairwise distances between all samples in ascending order, and then add edges between points according to this order until a connected graph G is constructed. The edge weight between Xi and $X j$ on this graph is denoted by wij. If there is an edge between Xi and $X j$, define the weight by $wij = exp[-d2(Xi , X j)/2\sigma 2]$, and if not, set $wi j = 0$, and set $W = (wi j)i j \in Rn\times n$. In the manifold ranking method, the cost function associated with ranking vector r is defined by

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

Where D is a diagonal matrix with $D_{ii} = \sum_{j=1}^{n} wij$ and $\mu>0$ is the regularization parameter. The first term in the cost function is a smoothness term that forces nearby points have similar ranking scores. The second term is a regularization term, which forces the query to have a rank close to 1, and all other samples to have ranks as close to 0 as possible. The ranking function r is the minimizer of $O(r)$ over all possible ranking functions.

This optimization problem can be solved in either of two ways: a direct approach and an iterative approach. The direct approach computes the exact solution via the closed form expression $r * = (In - \alpha S) -1 y$ where $\alpha = 1/1+\mu$, In is an $n \times n$ identity matrix and $S = D-1/2WD-1/2$. The iterative method is better suited to large scale datasets. The ranking function r is computed by repeating the iteration scheme $r (t + 1) = \alpha Sr(t) + (1 - \alpha)y,$ until convergence. The direct approach requires an $n \times n$ matrix inversion and the iterative approach requires $n \times n$ memory and may converge to a local minimum. In addition, the complexity of constructing the graph G is $O (n2 \log n)$. Sometimes a kNN graph is used for G, in which case the complexity is $O (kn2)$. Neither case is suitable for large-scale problems.

A weight matrix $Z \in Rd\times n$ which measures the potential relationships between data points in X and anchors in U. For convenience, denote by zi the i th column of Z. The affinity matrix W is then designed to be $ZT Z$. The final ranking function r can then be directly computed by

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

Where $H = ZD-1/2$ 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, in contrast to inverting the $n \times n$ matrix used in standard manifold ranking. When d _ n, as occurs in large databases, the computational cost of manifold ranking is significantly reduced. The complexity of computing the ranking function with the EMR algorithm is $O (dn+ d3)$. In addition, EMR does not require storage of an $n\times n$ matrix.

III. RESULTS AND DISCUSSION

Filtering method is to apply the 1D centered point discrete derivative for calculate gradient computation in vertical direction for vertical gradient and horizontal direction for horizontal gradient. Feature calculation using Histogram of Gradient Orientation and the Quantized levels for Hue, saturation, value. It is used to split and analyzes the character in individual plans. Color correlogram extracts the spatial information of pixels in the images. The Orientation defined Small image regions can be characterized as locally one dimensional e.g. interms of lines or edges.

IV. CONCLUSION

We have presented a novel algorithm for content-based multiple-query image retrieval where the queries all correspond to different image semantics, and the goal is to find images related to all queries. This algorithm can retrieve samples which are not easily retrieved by other multiple-query retrieval algorithms and any linear scalarization method. We have presented theoretical results on asymptotic non-convexity of Pareto fronts that proves that the Pareto approach is better than using linear combinations of ranking results.

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