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MEASURING PERFORMANCE OF IMAGE RETRIEVAL SCHEME "CLASSIFICATION"

A.Rama[1], Dr.C.Nalini[2]
Research Scholar, Department of CSE, Bharath University, Chennai[1]
Professor, Department of Computer Science and Engineering, Bharath University, Chennai [2]
rama_j1@yahoo.com[1], drnalinichidambaram@gmail.com[2]

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Abstract

Typical content-based image retrieval (CBIR) system query results are a set of images sorted by feature similarities with respect to the query. However, images with high feature similarities of the image may vary different from the query in terms of semantics. This is known as the semantic gap. We introduce a novel image retrieval scheme CLASSIFICATION for the retrieval of images by supervised learning which tackles the semantic gap problem based on a hypothesis: *semantically images tend to be classified in some feature space.* CLASSIFICATION attempts to capture semantic concepts by learning the way that images of the same semantics are similar and retrieving image classifications instead of a set of ordered images. In particular, CLASSIFICATION formed depend on which images are retrieved in response to the query therefore CLASSIFICATIONS give the algorithm as well as the user's semantic relevant as to where to navigate. CLASSIFICATION based image retrieval is a general approach that can be combined with any real-valued symmetric similarity measure. Thus it may be embedded in many current CBIR systems. Experimental results based on a database of about 60,000 images from COREL demonstrate improved performance.

Keywords: Content-based image retrieval, image classification, un-supervised learning, spectral graph classification.

I. Introduction

The steady growth of the Internet, the falling price of storage devices, and an increasing pool of available computing power make it necessary and possible to manipulate very large repository of digital information efficiently (CBIR) aims at developing techniques that support effective searching and browsing of large image digital libraries based on automatically derived image features. Although CBIR is still immature, there has been abundance of prior work. Due to space limitations, we only review work most related to which by no means represents the comprehension list. The remainder of the paper is organized as follows. It describes the general methodology of classification based image retrieval. It provides the experimental result. We conclude in section 4, together with a discussion of future work.

The major difference between CBICR and CBIR systems lies in the two processing stages, selecting neighbouring target images and image classification, which are the major components of classification. a typical CBIR system bypasses these two stages and directly outputs the sorted results to the display and feedback stage. figure 2 suggests that classification is the sorted similarity. this implies that classification may be embedded in a typical CBIR system regardless of the image features being used, the sorted method, and whether there is feedback or not. as a result in the following subsections, we focus on the discussion of general methodology of classification, and assume that a similarity measure is given.

2. Related Works

2.1. Neighbouring Target Images Selection

To mathematically define the neighbourhood of a point, we need to first choose a measure of distance. As to images, the distance can be defined by either a similarity measure (a larger value indicates a smaller distance). Because simple algebraic operations can convert a similarity measure into a dissimilarity measure, without loss of generality ,we assume that the distance between two im-ages is determined by a symmetric dissimilarity measure $d(i,j)=d(j,i)\geq 0$,name $d(i,j)$ the distance between images i and j to simplify the notation.

Next we propose two simple methods to select a collection of neighbouring target for query image i:

1. Fixed *radius method* (FRM) takes all target images within some fixed £ with respect to i. For a given query image, the number of neighbourhood target images is determined by £.
2. *Nearest neighbours method* (NNM) first chooses *k* nearest neighbours of *I* as seeds. The nearest neighbours for each seed are then found. Finally, the neighbouring target images are selected to be all the distinct target images among seeds and their *r* nearest neighbours.

If the distance is metric, both methods will generate similar results under proper parameters (£,*k* and *r*).How-ever, for non-metric distances, especially when the triangle selected by two methods could be quite different regardless of the parameters. This is due to the violation of the triangle inequality: the distance two images could be huge even if both of them are very close to a query image .The NNM is used in this work. Compared with the FRM, our empirical results show that, with proper choices of *k* and *r* the NNM tends to generate more structured collection of target images under a non-metric distance. On the other hand, the FRM because of the extra time to find nearest neighbours for all *k* seeds. The time complexity can be reduced at the price of extra storage space.

2.2 Organization of Classifications

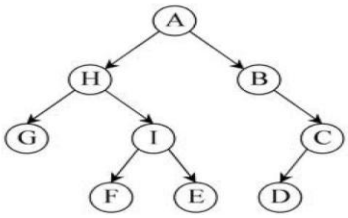


Fig:1 A tree generated by four Ncuts.

The recursive Ncut partition is essentially a hierarchical divisive classification process that produces a tree. For example Figure 2 shows a tree generated by four Ncuts. The first Ncut divides A into H and B. Since H has more no-des than B, the second Ncut partitions H into G and I. Next, I is further divided because it is larger than H and C. The fourth Ncut is applied to A, and gives the final four classifications (or leaves): G, F, E, D.The above example suggests trees as a natural organization of classifications. Nonetheless, the tree organization here may be misleading to a user because there is no guarantee of any correspondence between the tree and the semantic structure of images. Furthermore, organizing image classifications into a tree structure will significantly complicate the user interface. So, in this work, we employ a simple linear organization of classifications called traversal ordering: arrange the leaves in the order of a binary tree traversal (left child goes first). The order of two classifications produced by an Ncut iteration is decided by an arbitration rule: 1) let H and B be two classifications ge-nerated by an Ncut on A and d1 (d2) be the minimal distance between the query image and all images in H (B); 2)if d1<d2 then H is the left child of A, otherwise, B is the left child. Under the traversal ordering and arbitration rule, the query image is in the leftmost leaf since a classification containing the query image will always be assigned to the left child. For the sake of consistency, images within each classification are also organized in ascending order of distances to a query.

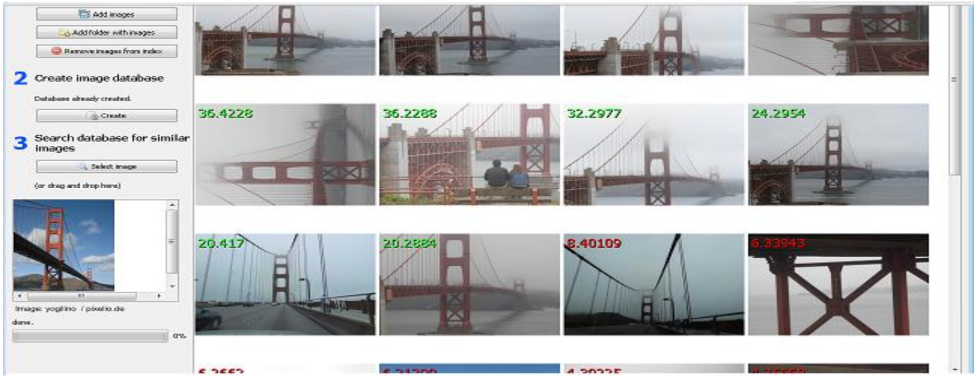
3. Experiments

Goodness of Image Classification: Ideally, CLASSIFICATION would be able to generate image classifications each of which contains images of similar or even identical semantics. The *confusion matrix* is one way to measure the number of classifications needs to be equal to the number of distinct semantics, which is unknown in practice.

Query Examples: Although we can force retrieval system to always generate 10 classifications in this particular experiment, the experiment setup would then be quite different to a real application. So we use *purity and entropy* to measure the goodness of image classification. Assume we are given a set of images belonging to c distinctive categories (or semantics) denoted by 1, c (in this experimental $c \leq 10$ depending on the collection of images generated by NNM) while the images are groups into m classifications Cj,j=1,..m .Purity for Cj is defined as P(Cj)=1/|Cj|

max|Cj,K| Where consists of images in Cj belongs to category k and |Cj| represents the size of the set. Each classification may contain images of different semantics. Purity gives the ratio of the dominant semantic class size in the classification to the classification size itself. The value of purity is always in the interval with a larger value means that the classification is a "purer" subset of the dominant semantic class. Since entropy considers the distribution of semantic classes in a classification, it is a more comprehensive measure than purity. Note that we have normalized entropy so that the value is between 0 and 1. Contrary to the purity measure, an entropy value near 0 means the classification is comprised mainly of 1 category, while an entropy value close to 1 implies that the classification contains a uniform mixture of all categories.

Classification Results



(a) Sunrise (b) ball (c) parrot (d) historical buildings.

This figure: Comparison of CLASSIFICATION and UFM. The query image is the upper-left corner image of each block of images. The underlined numbers below the images are the ID numbers of the images in the database. For the images in the left column, the other number is the classification ID (the image with a border around it is the representative image for the classification). For images in the right column, the other two numbers are the value of UFM measure between the query image and the matched image, and the number of regions in the image.

Retrieval Accuracy

For image retrieval, purity and entropy by themselves may not provide a comprehensive estimate of the system performance even though they measure the quality of image classifications. Because what could happen is a collection of semantic manically pure image classifications but none of them sharing the same semantics with the query image. Therefore one needs to consider the semantic relationship between these image classifications and the query image. For this purpose, we introduce the correct categorization rate and average precision. We call a query image being correctly categorized if the query category dominates the query image classification. The correct categorization rate, Ct, for image category t is defined as the percentile of images in category t that are correctly categorized when used as queries. It indicates how likely the dominant semantics of the first classification coincides with the query semantics. The fourth column of Table 1 lists estimations of CT for 10 categories used in our experiments. Note that randomly assigning a dominant category to the query image classification will give a Ct of value around 0.1 From the standpoint of a system user, Ctmay not be the most important performance index. Even if the first classification, in which the query image resides, does not contain any images that are semantically similar to the query image, the user can still look into the rest classifications. So we use precision to measure how likely an user would find images belonging to the query category within a certain number of top matches. Here the precision is computed as the percentile of images belonging to the category of query image in the first 100 retrieved images. The recall equals precision for this special case since each category has 100 images . The parameters in the NNM are set to be 30 to ensure that the number of neighbouring images generated is greater than 100. As mentioned in Section 2.5, the linear organization of classifications may be viewed as a structured sorting of classifications in ascending order of distances to a query image. Therefore the top 100 Retrieved images are found according to the order of classifications. The average precision for a category t is then defined as the mean of precisions for query images in category.

Speed: CLASSIFICATION has been implemented on a Pentium III 700MHz PC running Linux operation system. To compare the speed of classification with UFM [4], which is implemented and tested on the same computer, 100 random queries are issued to the demonstration web sites. CLASSIFICATION takes on average 0.8 second per query for similarity measure evaluation, sorting, and classification, while UFM takes 0.7 second to evaluate similarities and sort the results. The size of the database is 60, 000 for both tests. Although CLASSIFICATION is slower than UFM because of the extra computational cost for NNM and recursive Ncut, the execution time is still well within the tolerance of real-time image retrieval.

4. Conclusions and Future Work

This paper introduces CLASSIFICATION, a novel image retrieval scheme, based on a rather simple assumption: semantically similar images tend to be classified in some feature space. CLASSIFICATION tempts to retrieve semantically coherent image classifications from unsupervised learning of how images of the same semantics are alike. The empirical results suggest that this assumption seems to be reasonable when target images close to the query image are under consideration. CLASSIFICATION is a general approach in the sense that it can be combined with any real-valued symmetric image similarity measure (metric or non-metric). Thus it may be embedded in many current CBIR systems. The application of Classification based image retrieval to a database of 60,000 general-purpose images demonstrates that Classification based image retrieval can provide semantically more meaningful results to a system user than an existing CBIR system using the same similarity measure. Numerical evaluations show good classification quality and improved retrieval accuracy.

CLASSIFICATION based image retrieval has several limitations.

• The current heuristic used in the recursive Ncut always bipartitions the largest classification. This is a low-complexity rule. But it may divide a large and pure classification into several classifications even when there exists a smaller and semantically more diverse classification.

• The current method of finding a representative image for a classification does not always give a semantically accurate result. For the example in Figure 4(a), one would expect the representative image to be a bird image. But the system picks an image of sheep. If the number of neighbouring target images is large, scarcity of the unity matrix becomes crucial to retrieval speed. The current weighting scheme does not lead to a sparse a unity matrix.

One possible future direction is to integrate classification with keyword- based image retrieval approaches. Other graph theoretic classification techniques need to be tested for possible performance improvement. Classification may be combined with nonlinear dimensionality reduction techniques. CLASSIFICATION may also be useful for image understanding. As future work, we intend to apply Classification to search, browse, and learn concepts from digital imagery for Asian art and cultural heritages.

References

1. R. Baeza-Yates and B. Ribeiro-Neto, Modern Information Retrieval, Addison-Wesley, 1999.
2. K. Barnard and D. Forsyth, “Learning the Semantics of Words and Pictures,” Proc. 8th Int’l Conf. on Computer Vision, vol. 2, pp. 408–415, 2001.
3. C. Carson, S. Belongie, H. Greenspan, and J. Malik, “Blobworld: Image Segmentation Using Expectation-Maximization and its Application to Image Querying,” IEEE Trans. Pattern Anal. Machine Intell., vol. 24, no. 8, pp. 1026–1038, 2002.
4. Y. Chen and J. Z. Wang, “A Region-Based Fuzzy Feature Matching Approach to Content-Based Image Retrieval,” IEEE Trans. Pattern Anal. Machine Intell., vol. 24, no. 9, pp. 1252–1267, 2002.
5. I. J. Cox, M. L. Miller, T. P. Minka, T. V. Papathomas, and P. N. Yianilos, “The Bayesian Image Retrieval System, PicHunter: Theory, Implementation, and Psychophysical Experiments,” IEEE Trans. Image Processing,

vol. 9, no. 1, pp. 20–37, 2000.

6. C. Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic, and W. Equitz, “Efficient and Effiective Querying by Image Content,” J. Intell. Inform. Syst., vol. 3, no. 3-4, pp. 231–262, 1994.
7. G. H. Golub and C. F. Van Loan, Matrix Computations, 3rd ed., Johns Hopkins University Press, 1996.
8. Y. Gdalyahu, D. Weinshall, and M. Werman, “Self-Organization in Vision: Stochastic Classificationing for Image Segmentation, Perceptual Grouping, and Image Database Organization,” IEEE Trans. Pattern Anal. Machine Intell., vol. 23, no. 10, pp. 1053–1074, 2001.
9. A. Gupta and R. Jain, “Visual Information Retrieval,” Commun. ACM, vol. 40, no. 5, pp. 70–79, 1997.
10. M. A. Hearst and J. O. Pedersen, “Reexamining the Classification Hypothesis: Scatter/Gather on Retrieval Results,” Proc. of the 19th Int’l ACM SIGIR Conf. on Research and Development in Information Retrieval, pp. 76–84, 1996.
11. D. W. Jacobs, D. Weinshall, and Y. Gdalyahu, “Classification with Nonmetric Distances: Image Retrieval and Class Representation,” IEEE Trans. Pattern Anal. Machine Intell., vol. 22, no. 6, pp. 583–600, 2000.
12. J. Li and J. Z. Wang, “Automatic Linguistic Indexing of Pictures By a Statistical Modeling Approach,” IEEE Trans. Pattern Anal. Machine Intell., vol. 25, no.10, 2003.
13. J. Li, J. Z. Wang, and G. Wiederhold, “IRM: Integrated Region Matching for Image Retrieval,” Proc. 8th ACM Int’l Conf. on Multimedia, pp. 147–156, 2000.
14. W. Y. Ma and B. Manjunath, “NeTra: A Toolbox for Navigating Large Image Databases,” Proc. IEEE Int’l Conf. Image Processing, pp. 568–571, 1997.
15. S. Mehrotra, Y. Rui, M. Ortega- Binderberger, and T. S. Huang, “Supporting Content-Based Queries over Images in MARS,” Proc. IEEE Int’l Conf. on Multimedia Computing and Systems, pp. 632–633, June 1997.
16. A. Pentland, R. W. Picard, and S. Sclaro, “Photobook: Content-Based Manipulation for Image Databases,” Int’l J. Comput. Vis., vol. 18, no. 3, pp. 233– 254, 1996.
17. Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra, “Relevance Feedback: A Power Tool for Interactive Content - Based Image Retrieval,” IEEE Trans. Circuits and Video Technology, vol. 8, no. 5, pp. 644–655, 1998.
18. G. Sheikholeslami, W. Chang, and A. Zhang, “Sem Query: Semantic Classificationing and Querying on Heterogeneous Features for Visual Data,” IEEE Trans. Knowledge and Data Engineering, vol. 14, no. 5, pp. 988– 1002, 2002.