

An Efficient Relevance Feedback Technique for an Automatic Image Annotation

G.Kavitha ^{#1}, and C.Sasi kumar ^{*2}

Head of the department, Department of Computer Science and Engineering, Excel Engineering College

**Assistant Professor, Department of Computer Science and Engineering, Excel Engineering College*

Abstract- during the past few years, content based image retrieval (CBIR) has gained much attention for its potential applications in multimedia management. It is motivated by the explosive growth of image records and the online accessibility of remotely stored images. An effective search scheme is urgently required to manage huge image database. Different from the traditional search engine in CBIR, an image query is described by using one or more example images and low-level visual features(eg color, texture, shape, etc..) are automatically extracted to represent the image in the database. However the low-level features captured from the images may not accurately characterize the high-level semantic concepts. We proposed a new scheme of Sprinkling Relevance Feedback(SRF) for improving the performance and bridging the gap in CBIR, so we modified SVM called CLSVM (categorical label support vector machine) and compared with typical approach by query stretching (QS), we demonstrate that our suggest scheme can significantly improve the computation time and memory from the detailed view.

I. INTRODUCTION

In the content based image retrieval, the information which are important to transmit can be hidden inside the image, it based on the pixels, color etc., Users cannot identify the image with those contents, it may arise in many problems. So a new model of relevance feedback by sprinkling can be used to enhance it. The users may give a feedback for this technique, processing on them by classifying the positive and negative feedback. A positive feedback can steadily try to improve the performance and the negative feedback may involve neglecting the problematic issues and need to develop a new model. Another drawback is the unlabelled data, which can be easily eliminated that have to be carefully handled. All of them were processed using semi BMMA. But still it may show some difficulties in computation. For these purpose we modified a new scheme called SRF (Sprinkling relevance feedback) and QS(query stretching). The second section tells about system architecture the third section deals about the design goals and the next section deals with related works. The last section is conclusion.

II. RELATED WORKS

An information retrieval (IR) system locates information that is relevant to a user's query. Hirmath andpujari[3] proposed CBIR system based on several features by portioning the image into tiles. An IR system typically searches in collections of unstructured or semi-structured data. Similar to Moore's law of continual processor speed increase, there has been a consistent doubling in digital storage capacity every two years. The number of bits of information packed into a square inch of hard drive surface grew from 2,000 bits in 1956 to 100 billion bits in 2005[1]. With the growth of digitized unstructured information and, via high speed networks, rapid global access to enormous quantities of that information, the only viable solution to finding relevant items from these large text databases was search, and IR systems became ubiquitous. Matsumoto, R. Du Zhang, Meiliu Lu has authored a paper about image retrieval based on two methods. They are Support vector machine, Navie Bayes Classifier. . The content can be taken from the image with some of processing steps. The problem can be noticed that some of the image query can be left, so that the feedback can be collected from the user and it can be grouped into two categories positive and negative feedback, unlabeled data after performing it in relevance feedback if the result will be out of problem it can give the final results otherwise again it will do the operation as same as before and it needs to improve the computation time and memory then goes for SRF, CLSVM, QS. Then the final result can be noticed.

III. PROPOSED WORK

Our design goal contains two main methods of relevance feedback. First is Categorical label SVM and the next is Query Stretching.

Sprinkling RF:

In a CBIR system, user can demonstrates query that will result in a set of similar images. The images which are returned are not completely related to them. So they use SRF

again. To improve the learning methods, the relevance feedback model is repeatedly checks to attain the target. The query Stretching model can retrieve many other related images. A sampling model can be taken in order to process. Before introducing SVM, we clearly describe about how to sprinkle the relevance feedback output and can eliminate the gap between semantics. The relevance matrix can be taken in order to arrange the image database. The column in the SRF matrix represents the sample images and databases. The row represents the session number of the images.

SVM:

As a detailed history of classification, SVM describes the principle of Structured Rule Minimization (SRM) based on the Vapnik- Chervonenkis (VC) theory. It has powerful Generalization performance on many pattern classification problems. In General, given observation $(x, y) \in x^*y$, $i=1, \dots, l$ where $x \in R^n$ is the input space and $y_i \in Y$ is the associated label given a trusted source. It can be extracted by a training machine using a set of parameters, the test error of expectation is, $S(\alpha)$ is the future risk. The hyper plane in the SVM, as the trained data measures the different margin d , the hyper plane can be scaled as categorical label is engaged to find into products in $k(x_i, x_j) = \phi(x_i) \cdot \Phi(x_j)$.

CLSVM:

The labels of the data are from the authentic source, if they may arise on some critical data it generates the previously computed decision. By reducing the risk from it, we may introduce a confidence degree of data in SVM and recommended in CLSVM as follows.

Given a categorical label c , the corresponding unordered label set U can be as,

$$U = \{i \mid i = \{+1, -1\}\} \quad L(x, Y, s, \chi, \xi, \mu, \omega) = 1/2 \|x\|^2$$

Dual optimization problem is $\min_{\alpha} \frac{1}{2} \sum_i \alpha_i \xi_i + \sum_j y_j \alpha_j$

$$\sum_i \xi_i y_i = 0 \quad \sum_i \xi_i y_i > 0$$

IV. ALGORITHM

GRF algorithm:

It is similar to SVM of building relevance feedback model of positive and negative with confidence degrees. Based on the query, a set of n samples are given to the users. It begins a query part of QS, the total samples are consider as group of basic seeds. To attack the problem, use implement relevance feedback by a labeled value of m , n for each image m with respect to seed n , obtained by normalizing.

$$Q_{nm} = \{ S_{m,n} \mid \max_n S_{m,n} \}$$

$$\{- S_{m,n} \mid \min_n S_{m,n} \}$$

$$\text{If } S_{m,n} > 0, < 0, = 0.$$

Query Stretching:

Based on the user query, it searches for the relevant set of images and processing on them to display only the images which are closely similar to the user content. By Processing on the query it show different set of images, but some of them are not dissimilar to that so being processes have to be

refining again and again to get the original set of relevant images.

V. CONCLUSION AND FUTURE WORK

The CBIR can be implemented by modified CLSVM to attain more efficient. This model also reduces the computation time and memory by combining with above methods. Further it may develop to increase the performance and make the content based image retrieval as a powerful implementing the tools with minimum computation process.

VI. REFERENCES

- [1] W. Yang, C. Sun, H. S. Du and J. Yang, "Feature extraction using Laplacian maximum margin criterion," *Neural Process. Lett.*, vol. 33, no. 1, pp. 99-110, Feb. 2011.
- [2] J. Chen, S. Shan, G. Zhao, X. Chen and W. Gao, "Matti Pietikainen, WLD: A robust descriptor based on weber's law," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 9, pp. 1705-1720, Sep. 2010.
- [3] P. S. Hiremath and J. Pujari, "Content based image retrieval based on color feature using Image and its complement," 15th International Conference on Advance Computing and Communication.
- [4] X. He, D. Cai and J. Han, "Learning a maximum margin subspace for image retrieval," *IEEE Trans. Know. Data Engg.*, vol. 20, no. 2, pp. 189-201, Feb. 2008.
- [5] W. Bian and D. Tao, "Biased discriminant Euclidean embedding for content based image retrieval," *IEEE Trans. Image Process.*, vol. 19, no. 2, pp. 545-554, Feb. 2010.
- [6] Peter Auer, Zakria Hussain, Samuel Kaski, Arto Klami, Jussi Kujala, Jorma Laaksonen, Alex P. Leung, Kitsuchart Pasupa, John Shawe-Taylor "Pinview: Implicit Feedback in Content-Based Image Retrieval" *JMLR: Workshop and Conference Proceedings*, Workshop on Applications of Pattern Analysis, pp. 51-57, 2010.
- [7] X. Zhou and T. Huang, "Relevance feedback for image retrieval: A comprehensive review," *Multimedia Syst.*, vol. 8, no. 6, pp. 536-544, Apr. 2003.
- [8] Dorota G. Iowacka, John Shawe-Taylor "Content-based Image Retrieval with Multinomial Relevance Feedback" *JMLR: Workshop and Conference Proceedings*, 2nd Asian Conference on Machine Learning (ACML2010), Tokyo, Japan, pp. 111-125, Nov. 8-10, 2010.
- [9] Ja-Hwung Su, Wei-Jyun Huang, Philip S. Yu, and Vincent S. Tseng "Efficient Relevance Feedback for Content Based Image Retrieval by Mining User Navigation Patterns," *IEEE Trans. On Knowledge and Data Engg.*, Vol. 23, No. 3, pp. 360-372, March 2011.
- [10] Shahrooz Nematipour, Jamshid Shanbehzadeh, Reza Askari Moghadam "Relevance Feedback Optimization in Content Based Image Retrieval Via Enhanced Radial Basis Function Network" *Proceedings of the International MultiConference of Engineers and Computer Scientists*, Vol. 1, IMECS 2011, March 16-18, 2011, Hong Kong.