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Image Retrieval By Semi Supervised Biased Maximum Margin Analysis

Engineering

KEYWORDS : CBIR, QBE, RF, NPRF, Support Vector Machine (SVM)

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ABSTRACT

Many real time applications need image search. Such applications facilitate Query by Example (QBE). User gives an input image and the system retrieves relevant images. The features of input image are used in the query processing. This concept is known as CBIR (Content Based Image Retrieval). Considerable research has been carried out in this area to improve the accuracy of image retrieval. The existing systems used relevant feedback to improve the quality of CBIR. Many RF based schemes came into existence. Out of them SVM based RF has become popular. Its drawback is that it does not see difference between positive and negative feedbacks. Moreover it also ignores unlabeled samples. The SemiBMMA (Semi Supervised Biased Maximum Margin Analysis) proposed by Shang et al. addresses this problem. This paper further improves SemiBMMA by integrating it with Navigation Pattern Based Relevance Feedback (NPRF). Experiments made with prototype application revealed that the SemiBMMA with NPRF requires very less number of iterations to get user-satisfied results.

I. INTRODUCTION

Much research went into image retrieval systems. CBIR systems allow efficient retrieval of images based on given input query. In systems where multimedia files are to be searched, the CBIR is required [1], [2].

The usage of CBIR is essential as the bulk of images added to the electronic database of WWW. Effective CBIR is required to process requests accurately. Low level features are used by initial CBIR to retrieve images. The features include texture, color and shape [3], [4], [5], [6], [7], [8], [9], [10].

However, the low level features can't deal with high level semantics [12]. This made a gap between them. Relevance Feedback (RF) is used to overcome this drawback [12], [13]. To improve quality of CBIR query movement and query reweighting techniques are used in [14], and [15].

Later on SVM (Support Vector Machine) and self-organizing map were used in [16] and [17]. They used only positive feedbacks. Biased SVM overcomes this problem by using positive and negative feedbacks [18]. In [19] and [20], manifold learning approaches were introduced. "*All positive examples are alike; each negative example is negative in its own way*" is an important observation regarding CBIR. In [21], [22] and [23] user choices are allowed as positive while others are considered negatives automatically.

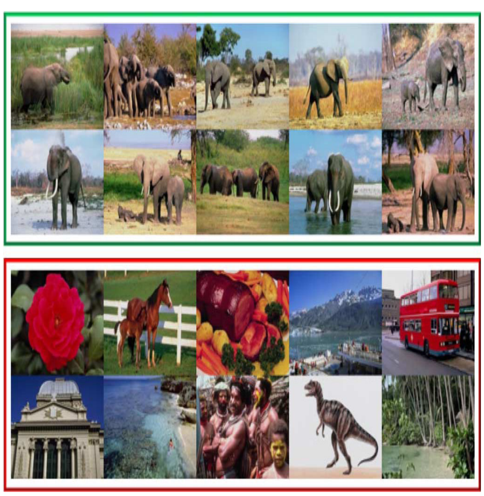

Fig. 1 – Positive and Negative Samples

CBIRs with RF mentioned above have drawbacks as they use either heuristics or ignore negatives, or suffer from small sample size.

Later on RFs based on classification were used [24]-[26]. Afterwards in [25]-[29] two – class SVM was used. SVM RF methods used only positive feedbacks. Direct usage of it deteriorates quality of CBIR. This is due to the fact that images can belong to different subspaces. To overcome the problem Biased Maximum Margin Analysis (BMMA) and Semisupervised BMMA techniques were used. They used positive and negative samples to achieve more accurate results. This paper further improves performance of SemiBMMA by integrating it with Navigation Pattern Based Relevance Feedback (NPRF). The prototype application built by us is used to make experiments. The results revealed that the proposed CBIR system converges faster with less number of iterations.

The remainder of this paper is organized into some sections. Section II reviews relevant literature. Section III provides details about Proposed CBIR system. Section IV provides details about empirical results while section V concludes the paper.

II. PRIOR WORK

In research and academic circles there was lot of attention on content based image retrieval. This is due to the requirement of various real world applications. SVM based RF systems [25]-[27], [29], [30] when used directly could not improve performance as they ignore unlabeled samples and do not use negative samples. Afterwards Graph Embedding Frameworks including [31] came into existence. The latest technique is SemiBMMA proposed by Zhang et al. [1] which uses unlabelled samples along with positive and negative feedbacks. In this paper we improve SemiBMMA by integrating it with Navigation Pattern Based Relevance Feedback (NPRF). The proposed system fills the gap between low level visual features and high level semantics completely. In less feedback iterations, the system gets user-satisfied results.

III. PROPOSED CBIR SYSTEM

The proposed NPRF scheme that integrates with SemiBMMA proposed by Zhang et al. is discussed in this section.

SemiBMMA

"All positive examples are alike; each negative example is negative in its own way" is an important observation. Based on this, Zhang et al. developed CBIR scheme known as SemiBMMA. This has improved performance of CBIR. Prior to this the CBIR systems used SVM based RF schemes. They were not efficient as they do not consider negative examples and unlabelled samples.

As SemiBMMA considers negative feedbacks and unlabeled samples, its performance is better. It could reduce the number of feedbacks required. Algorithm used in SemiBMMA is presented in fig. 2.

INPUT: $X=\{X_1, X_2, \ldots\ldots\ldots X_N\} \in Rh$ stand for all the feedback samples and unlabeled samples, which include the positive sample set X +, the negative sample X- and unlabeled samples

1) Construct the supervised intrinsic graph G, according to the formulation and calculate the matrix value XLXt.
2) Construct the supervised penalty graph G, according to the formulation and calculate the matrix value XBXt.
3) Construct the laplacian regularizer according to the formulation and calculate the matrix value XUXt.
4) Calculate the projection matrix α according to Generalized Eigenvalue Decomposition on the matrix X(B-L-β*U)Xt.
5) Calculate the new representations: project all positive, negative and remaining samples in the database onto the reduced subspace respectively, i.e., $Y^+=a^TX^+, Y^-=a^TX^-$

OUTPUT: Positive and negative samples, Y^+ and Y^-, in this reduced space

Fig. 2 –SemiBMMA algorithm [1]

As shown in fig. 2, the algorithm used in SemiBMMA uses unlabelled samples also along with positive and negative samples. The negative samples reduce the search space. The unlabelled samples are converted to labeled samples to reduce search space further. This fills the gap between low level visual features and high level semantics.

Proposed RF Scheme

The proposed scheme integrates semiBMMA with NPRF. The NPRF mines the navigational patterns of users in order to achieve faster convergence. The offline knowledge discovery from navigational patterns is done using algorithm proposed by Su et al. [32]. This algorithm takes navigation logs as input and generates patterns that can be used in the proposed scheme. The overview of the proposed CBIR is as shown in fig. 3.

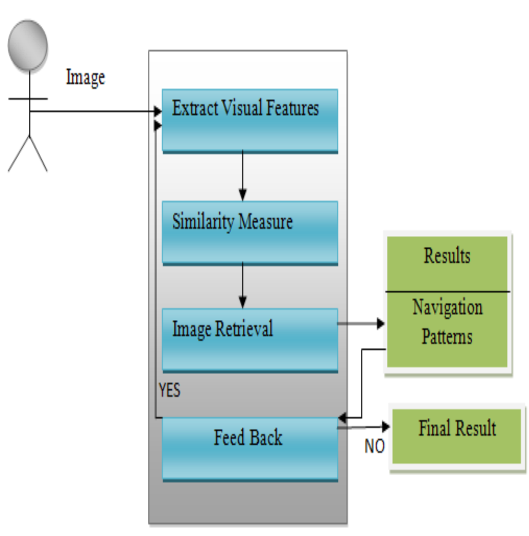

Fig. 3 – CBIR with NPRF and SemiBMMA

As shown in fig. 3, end user gives initial query. The CBIR uses low level visual features of the image to process query. Then SemiBMMA algorithm is applied in order to support user feedback. The system considers positive samples, negative samples and also unlabelled samples to process query. In the process, it also uses NPRF along with feedbacks of SemiBMMA for faster convergence. User gets satisfactory images in less number of iterations. Thus the proposed scheme performs better than existing systems. It is evident in the experimental results presented in section IV.

IV. EXPERIMENTAL RESUTLS

The environment used to build prototype application includes a PC with Core 2 Dual processor and 4 GB or RAM. The application is built with GUI using Java programming language. IDE used for building application is NetBeans.

Image Database

From Internet sources around 3000 images were collected. They belong to various categories such as flowers, animals and so on. They are used to test the prototype application.

Fig. 4 – Sample Image Categories in Database

The results of various queries are recorded. They are compared with SemiBMMA. The results show that the new scheme proposed in this paper outperforms the SemiBMMA with higher performance. The reason is that it makes use of NPRF along with positive, negative, and unlabelled samples.

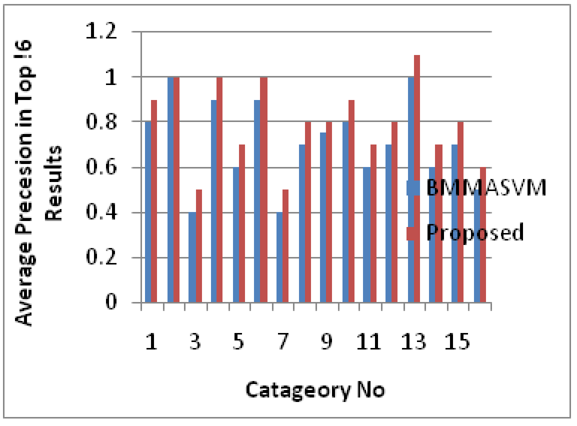

Fig. 5–Average precision in the top 16 results of after two rounds of feedback

As shown in fig. 5, the proposed approach is compared with SemiBMMA. The graph shows that the proposed system has more precision. The graph shows results of various image categories in terms of average precision of top 16 results after two rounds of initial feedback.

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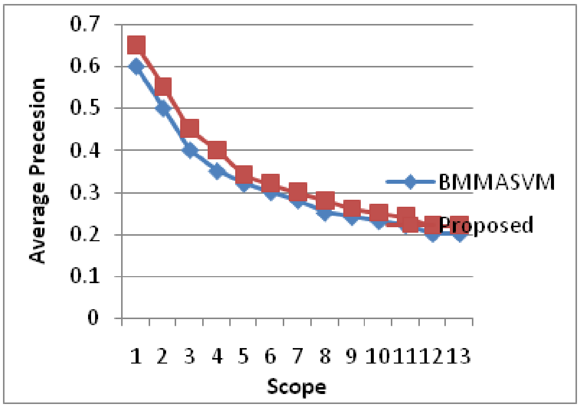

Fig. 6 – Precision and scope curve after first feedback

As shown in fig. 6, the precision of SemiBMMA and proposed scheme is presented. As shown in graph the proposed scheme performs better than the SemiBMMA.

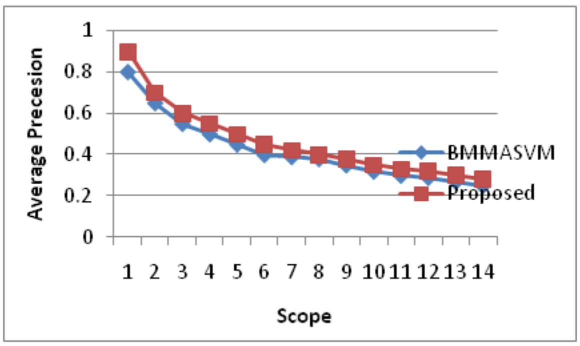

Fig. 7 – Precision and scope curve after second feedback

As shown in fig. 7, just after second round of feedback precision of both schemes is presented. The proposed scheme's precision is better than the existing one.

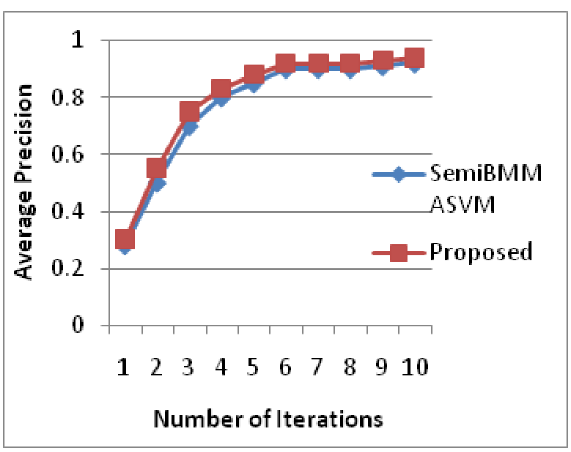

Fig. 8 – Average precisionin top 10 results

As shown in fig. 8 the precision of proposed RF scheme and that of SemiBMMASVM is presented. The top 10 results are considered. As shown in figure the performance of proposed is better than the existing one.

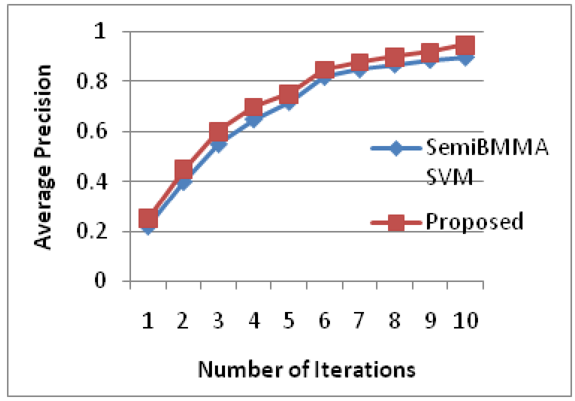

Fig. 9 – Average precision in top 20 results

As shown in fig. 9 the precision of proposed RF scheme and that of SemiBMMASVM is presented. The top 20 results are considered. As shown in figure the performance of proposed is better than the existing one.

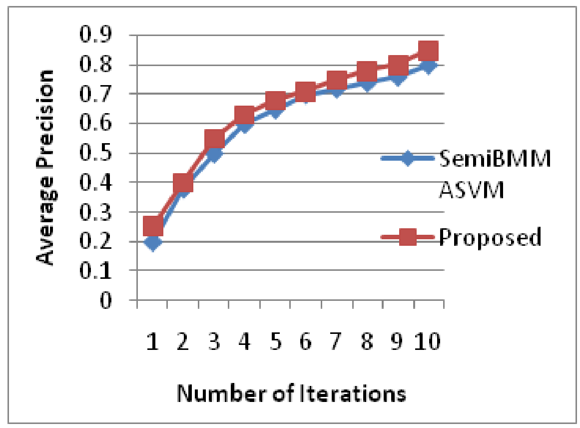

Fig. 10 – Average precision in top 30 results

As shown in fig. 10 the precision of proposed RF scheme and that of SemiBMMASVM is presented. The top 30 results are considered. As shown in figure the performance of proposed is better than the existing one.

V. CONCLUSION

In this paper we proposed new RF scheme which known as Navigation Pattern Based Relevance Feedback. We combine this scheme with SemiBMMA proposed by Zhang et al. for best performance. We have built a prototype application to test the efficiency of the proposed scheme. The results revealed that it outperforms existing schemes. It achieves faster convergence by retrieving user-satisfied images in less number of iterations. The reason for this performance is due to the usage of positive feedbacks, negative feedbacks, unlabelled samples, and navigational patterns.

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