CONTENT BASED IMAGE RETRIEVAL ASSOCIATE WITH THE INTERSECTION OF MULTI KERNAL RELEVANCE VECTOR MACHINE AND HISTOGRAM JOIN

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Abstract- Relevance Feedback is an important tool for grasping user's need in Interactive Content Based Image Retrieval (CBIR). Keeping this in mind, we have build up a framework using Relevance Vector Machine Classifier in interactive framework where user labels images as appropriate and inappropriate. The refinement of the images shown to the user is done using a few rounds of relevance feedback. This appropriate and inappropriate set then provides the training set for the RVM for each of these rounds. The method uses Histogram Intersection kernel with this interactive RVM (IKRVM). It has a retrieval component on top of this which searches for those images for retrieving which falls in the nearest neighbor set of the query image on the basis of histogram intersection based identical ranking (HIIR). The experimental results shows that the proposed framework shows better precision when compared with Active learning based RVMActive implemented with Radial Basis or Polynomial Kernels.

Keywords: *Histogram intersection similarity measure, relevance vector machines, Intersection kernel, content based image retrieval, active learning.*

1. INTRODUCTION

Relevance feedback and active learning based CBIR has been a research topic recently [1]. RVM can be formulated and solved within a completely Bayesian paradigm through the use of variational inference, thereby giving a posterior distribution over both parameters and hyperparameters. We demonstrate the practicality and performance of the variational RVM using both synthetic and real world examples. There exist different methodologies for sparse linear regression, including least absolute shrinkage and selection operator (LASSO) [1],[2] and support vector machines (SVM) [3]. In a Bayesian approach such as RVM, sparseness is achieved by assuming a sparse distribution on the weights in a regression model. Specifically, RVM is based on a hierarchical prior, where an independent Gaussian prior is defined on the weight parameters in the first level, and an independent Gamma hyperprior is used for the variance parameters in the second level. This results in an overall student prior on the weight parameters, which leads to model sparseness. A similar Bayesian methodology to achieve sparseness is to use a Laplacian prior [5][7], which can also be considered as a two-level hierarchical prior, consisting of an independent Gaussian prior on the weights and an independent exponential hyperprior on their variances.

In this work we have designed an interactive CBIR with relevance feedback which uses IKRVM integrated with ranking based retrieval using HIIR. The novelty of the method lies in developing a CBIR framework when less number of labeled training instances is available and resource utilization has to be made efficient as well as retrieved images should be more similar to query image.

The paper contains 4 following sections. Section 2 and 3 contains the RVM theory and feature extraction module and Section 4 holds the proposed method. Experimental results are given in section 5 with comparison. The paper completes with conclusion and discussions in Section 6.

2. RVM THEORY

2.1. Multi-kernel Relevance Vector Machine

Relevance vector machine (RVM) is a special case of a sparse linear model, where the basis functions are formed by a kernel function☐ centred at the different training points:

$$y(x) = \sum_{i=1}^{N} w_i (x - x_i) \quad 1$$

While this model is similar in form to the support vector machines (SVM), the kernel function here does not need to satisfy the Mercer's condition, which requires ☐to be a continuous symmetric kernel of a positive integral operator. Multi-kernel RVM is an extension of the simple RVM model. It consists of several different types of kernels , given by:

$$y(x) = \sum_{i=1}^{M} \sum_{j=1}^{N} w_{mi\,m} (x - x_i) \quad 2$$

The sparseness property enables automatic selection of the proper kernel at each location by pruning all irrelevant kernels, though it is possible that two different kernels remain on the same location.

2.2. Sparse Bayesian Prior

A sparse weight prior distribution can be obtained by modifying the commonly used Gaussian prior in (5), such that a different variance parameter is assigned for each weight:

$$p(w \mid \propto) = \prod_{i=1}^{M} N(w_i \mid 0, \propto_i^{-1}) \qquad 3$$

where is   ) vector consisting of *M* hyperparameters, which are treated as independent random variables. A Gamma prior distribution is assigned on these hyperparameters:

$$p(\;)=F=Gamma\;(\;a\;,b\;)$$

where *a* and *b* are constants and are usually set to zero, which results in a flat Gamma distribution.
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3 FEATURE EXTRACTION

We calculate both Color and Texture features for each image in the database. For color feature extraction histogram based feature extraction by binning the pixel values based on RGB color space using a novel approach is done. RGB color space does not provide any information of image brightness. So we converted the pixels in each bin from RGB to HSV. In each bin, for each of H, S and V channel statistical moments like mean and variance are calculated. Using spare weight prior Gaussian distribution of average and average variance, spread of bin and elongation of bin are calculated. For texture feature extraction purpose, we first obtain the discrete wavelet transformed version of a given image using haar wavelet mask. From an image of resolution M x N, the haar wavelet transform obtains sub images in four different orientation each of resolution M/2 x N/2. From these 4 sub images, we calculate the grey level co-occurrence matrix (GLCM). The energy measures for the 4 GLCMs are calculated as follows

$$Energy =$$

Where (i,j) represents the row and column pair of each GLCM representation by   where d represent the displacement of GLCM. The energy spread and energy elongations are calculated from Gaussian distribution of energy mean and energy variance.

4 PROPOSED METHOD

Initially we have a parent database of images containing *C* categories of images, each category having p number of images. The training set *Tr* is formed from this parent database by selecting randomly *r* *(r<p)* images for each of the category. Hence *Tr* has total *rxC* images. The rest of the images in the database form the test set *Ts*. Hence *Ts* has total *(p-r)xC* images.

4.1 Training by IKRVMActive

The system starts when user selects an image from *Ts* in the querying phase. The next phase is the relevance feedback which starts after the querying phase. Then a fixed number (*k*) of images are selected randomly without replacements from *Tr* and kept in set *F*. User is shown the set *F* which he marks as relevant or irrelevant. Relevant images form set *Rr* and irrelevant images form set *Ri*. The next phase is the training of IKRVM. Here calculation of feature vector of *Rr*and *Ri* is done. Feature vectors of *Fr* forms the positive set and feature vectors of *Fi* forms the negative set of data points for training the classifier. When they are input to IKRVM, it draws a hyperplane separating them.

The feature set of *Tr* is calculated and then fed to IKSVM for classification so that the hyperplane formed can separate data points in training set as positive or negative .Those data points which falls on the positive side of the hyperplane forms a set *FTr* and similarly the negative side forms another set *FTi*. Since an image is a data point in a feature space we use the term data point and feature vector interchangeably. The selection of sample images for next feedback round is the task of the next phase.

In this phase *k/2* data points which are the most nearest to the hyperplane are selected from the set *FTr* and similarly *k/2* data points are selected from the set *FTi*. The images corresponding to these *k* data points are kept in set *F*. If this is not the final iteration then the process continues again from step of showing images of the relevance feedback phase up to this step. Otherwise the process continues from the same step up to the completion of training of IKRVM phase and then goes to retrieval phase discussed in next subsection. The advantage of using IKRSVM is that in the generalization phase the time complexity can be approximated to be proportional to number of dimensions of the feature vector and devoid

4.2 Retrieval Using Histogram Intersection similarity Measure

Field   Sea   Sunset   White Rose   Red Rose   Sunflower
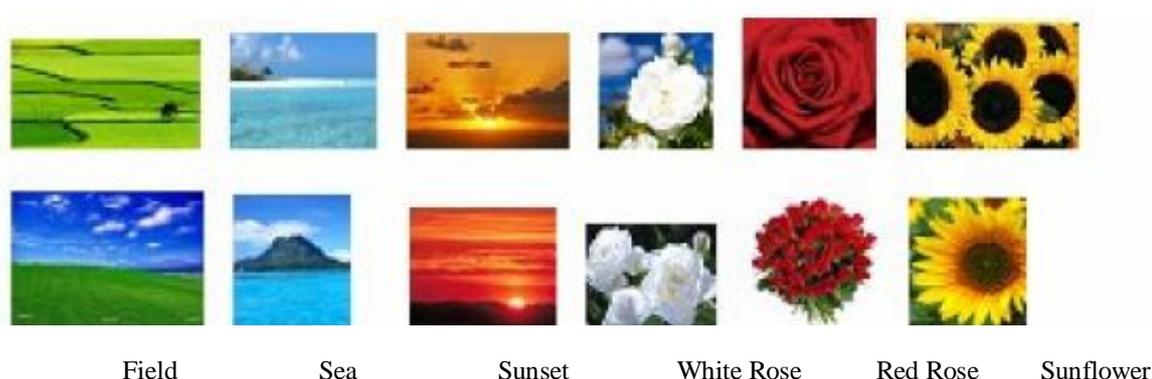
Fig. 1. Sample Images of each category from the database

Step 1: Starts by collecting the set F*Tr* from the last iteration of training by IRSVM*Active*

Step 2: Calculate the feature vector of the query image

Step 3: Then the query image feature vector is plotted along with all the data points in *FTr* in a d dimensional space.

Step 4: To get N number of images from the database which are most relevant to the query image, to be displayed.

Step 5: On the basis of HISM calculation of the distance of query data point with data points in
the set F*Tr* is done.

Step 6: Lastly sorting of the distances in descending order is done.

This follows from the fact that two of the most relevant images will have histogram distance close to 1 and the dissimilar ones will have distance close to 0. Finally retrieval of first N images from that sorted list is done.
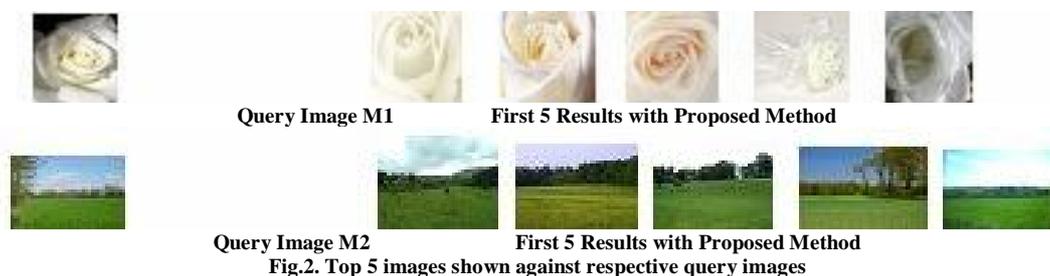

Query Image M1   First 5 Results with Proposed Method

Query Image M2   First 5 Results with Proposed Method

Fig.2. Top 5 images shown against respective query images

5 EXPERIMENTAL RESULTS

We have done our experiments on a 6 category image database having 120 images per category. Each category has some overlapping RGB values with other categories. The training set is computed by randomly collecting 80 images from each category. The test set contains remaining 40 images from each category. Fig 2 shows the first 5 retrieved images ordered according to the HISM ranking against two query image from two different categories. One of the performance measures for image retrieval is

precision which is defined as *(Number of relevant images retrieved)/ (No of images retrieved).* The graph in fig 3 shows that the proposed method performs better than other 3 methods for instance when 20 images are retrieved the proposed method has 100% precision whereas RVMActive used with Radial Basis kernel gives 95% precision, with polynomial degree 2 kernel gives 85% precision and with polynomial degree 4 kernel gives 65% precision
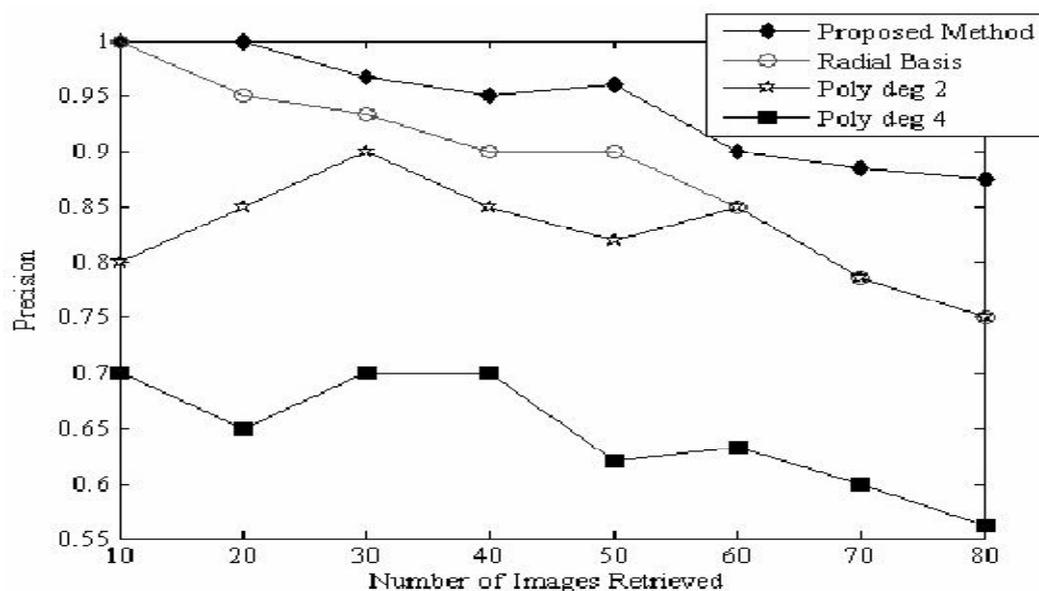
Fig. 3. Comparative study of existing Multi kernel functions used with SVM & the Proposed Method after 3 feedback rounds

6 CONCLUSION AND DISCUSSIONS

Our proposed method performs well off even when the number of images retrieved is close to the number of relevant images in the database. The method is also very efficient in terms of time complexity. The time complexity in the test phase of RVM is reduced due to using histogram intersection kernel based RVM. Also, since the RVM training complexity is dependent on number of training instances, we have sampled the database and reduced the number of training instances by using the relevance feedback rounds. This mechanism is suitable for reducing the training complexity for large databases. A future direction of research may be to use large databases and efficiently sub sampling them for using the proposed method and the results could be verified.

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