Survey of Relevance Feedback methods in Content Based Image Retrieval

Darshana Mistry

Gandhinagar Institute of Tehcnology college
Gujarat University

***Abstract*—In content Based Image Retrieval, images are retrieved based on color, texture and shape (low level perception). There is a gap between user semantics (high level perception) and low level perception. Relevance feedback (RF) learns association between high level semantics and low level features. Bayesian method, nearest neighbor search method, Log based RF, Support Vector Machine (SVM) is methods of Relevance Feedback. Bayesian method is good for understand but it is not worked for fast access. In nearest neighbor search method, data are compressed. So some times images may be lost its features. Log based method are used soft label using SVM. SVM is best method for RF because it works on structure risk minimization by VC dimensions.**

***Index Terms*— Relevance Feedback, RF, Support Vector Machine, SVM**

I. Introduction

Content-based document image retrieval(CBIR), a technique which uses visual contents to search images from large scale image databases according to users' interests, has been an active and fast advancing research area since the 1990s. During the past decade, remarkable progress has been made in both theoretical research and system development.

In Content-based image retrieval, uses the visual contents of an image such as color, shape, texture, and spatial layout to represent and index the image[2]. In typical content-based image retrieval systems (Figure 1), the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities distances between the feature vectors of the query example and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaning full retrieval results.

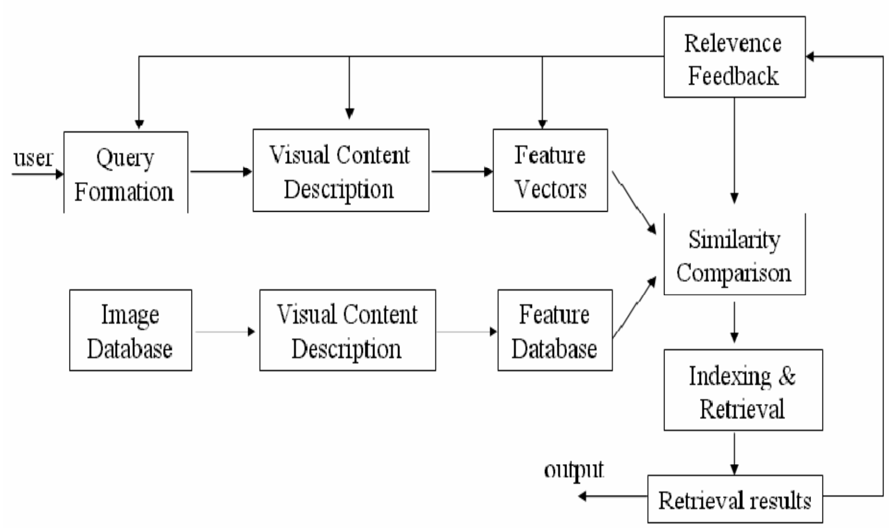


Fig. 1. Diagram of content based image retrieval

II. Relevance Feedback

In CBIR, images are extracted based on features vector. Typical features include pixel color histogram, gray scale histogram, texture features and edge-content measures. Some features may be meaning less to user or may be highly correlated to other features. Some features may be useful for certain queries but may be lose significance for other features. The notion of similar in the mind of user may fluctuate depending on the query, the history of retrieval, and the user.

Relevance feedback (RF) learns the associations between high level semantics and low level features. In a typical, RF system, given a set of retrievals for an image query, the user identifies relevant and non-relevant examples. Based on these
examples, the similarity metric is modified to re-compute the next set of retrievals. Relevance feedback originated from text-based information retrieval is a powerful technique to improve the retrieval performance.

There are different methods of relevance feedback:

- Bayesian Network
- Nearest Neighbor Search method
- Log based Relevance feedback
- Support Vector Machine

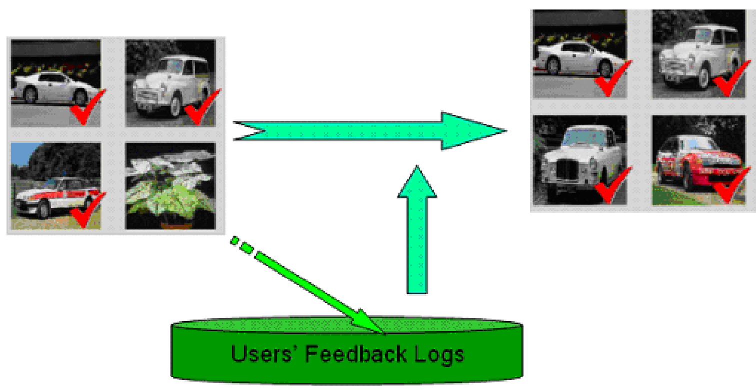


Fig.2. Relevance Feedback

A. Bayesian Network

In CBIR systems which extract visual features from the images automatically. Similarities between two images are measured in terms of the differences between the corresponding features. During the process of image retrieval, the user specifies the relevance of the retrieved objects, and the system will then refine the query results by learning from this information. Since the feedback information from the previous iterations and the next iteration does not directly connect, the major problem of their approach is that when the next iteration of retrieval is started the information from previous iterations is almost lost.

Bayesian network as a relevant image adoption model to select a number of good points composing the positive feedback information[11]. It is based on the evaluation of the belief values of the relevant image nodes in the network such that these belief values can be used as probabilistic measure of usability of the relevant images. As Figure 3, the network consists of three layers: query layer, feature index layer and relevant image layer. The root node is the query layer representing the query example image given by the user. The intermediate layer is feature index layer which can be further divided into two levels. The first level contains low-level feature representations, such as color, texture and shape. The second level is composed by the components of the feature vectors. The relevant image layer consists of the individual relevant images specified by the user. The network is different with various query examples and different relevant images. New specified relevant images get added to the relevant image layer as we move from one iteration of feedback to the next. All nodes in the network are associated with a belief value and all the direct connections between the nodes are associated with a link weight, which is represented by a conditional probability. After the initial feedback, all the relevant images are used to build the Bayesian network and the link weights are calculated. Perform the inference propagation to update the belief values of all the nodes in the network. Select the relevant images whose belief is above the threshold as the positive feedback information. Update the link weights using the chosen relevant images. The updated belief values are set as new prior beliefs for the next iteration. Start a new iteration of retrieval using the updated positive feedback information. If user get result as his requirement then stop process otherwise continue this process.

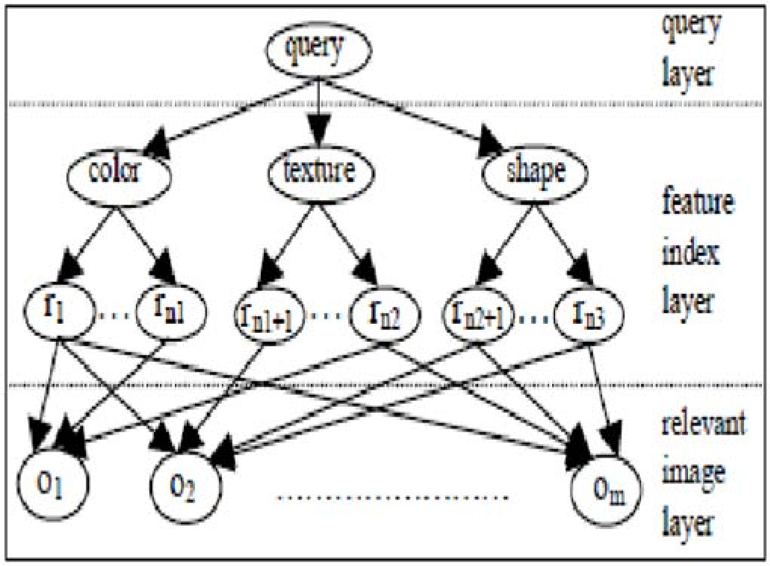


Fig.3. Bayesian Network

B. Nearest Neighbor Search Method

In nearest neighbor search for relevance feedback, the basic idea behind this method is to constrain the search space for the nearest neighbors for the next iteration using the current set of nearest neighbors[10]. In content based retrieval, to retrieve images that are similar in texture or color, usually one computes the nearest neighbors of the query feature vector in the corresponding feature space. Given a collection of image or video data, the first step in creating a database is to compute relevant feature descriptors to represent the content. The user identifies a set of retrieval examples relevant to the image, and that information is then used to compute a new set of retrievals. One approach to computing a new set of retrievals closer to the users expectation is to modify the similarity metric used in computing the distances between the query and the database items. The distance between two feature vectors is typically calculated as a quadratic distance of the form (Q-F)TW(Q-F)where Q is a query vector, F is a database feature vector, and W is a positive semi-definite matrix. During each iteration, the weight matrix is updated based on the users feedback. Given the updated weight matrix, the next set of nearest neighbors is then computed. There are more recent methods, such as kernel-based approaches that appear to be more effective for learning but they are computationally prohibitive for large data sets in high dimensions.

The online relevance feedback from users is collected and stored in a log database. When feedback log data is unavailable, the log-based relevance feedback algorithm behaves exactly like a regular relevance feedback algorithm, *C. Log based Relevance Feedback*

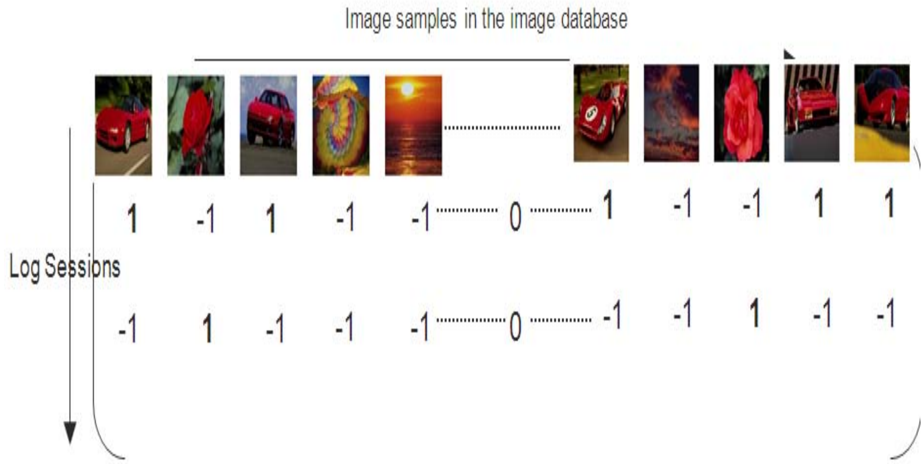


Fig. 4. Log based relevance feedback

which learns the correlation between low-level features and users' information needs through the feedback image examples. When feedback log data is available, the algorithm will learn such correlation using both the feedback log data and the online feedback from users.

Using of Relevance Matrix (RM), in each log session, images are marked as relevant images (+1) and non-relevant images(-1) and unknown(0).

For every two images, ***i*** and ***j***, their relationship can be measured by a modified correlation function:

$$R_{ij} = \sum_k \delta_k \cdot RM(k,i) \cdot RM(k,j) \qquad (1)$$

$$\delta_k = \begin{cases} 1, if RM(k,i) + RM(k,j) \geq 0 \\ 0, if RM(k,i) + RM(K,j) \leq 0 \end{cases} \qquad (2)$$

For an initial positive sample ***i***, the relevance degree between every image sample ***j*** of the database are computed by a soft label function:

$$s_j^i = \begin{cases} R_{ij} / \max_j R_{ij} \; if R_{ij} \succ 0 \\ -R_{ij} / \max_j R_{ij} \; if R_{ij} \prec 0 \end{cases} \qquad (3)$$

To find soft label, we have to use soft label support vector machine algorithm.

D. Support Vector Machine

Support Vector Machines (SVM) is an approximate implementation of the structural risk minimization (SRM) principle[12][13][14]. It creates a classifier with minimized Vupnik- Chervonenkis (VC) dimension. SVM minimizes an upper bound on the generalization error rate[14]. The error rate is bounded by the sum of the training-error rate and a term that depends on the VC dimension. The SVM can provide a good generalization performance on pattern classification problems without incorporating problem domain knowledge.

Consider the problem of separating the set of training vectors belonging to two classes, e.g., image retrieval problem, +1 denotes positive example, -1 denotes the negative example.

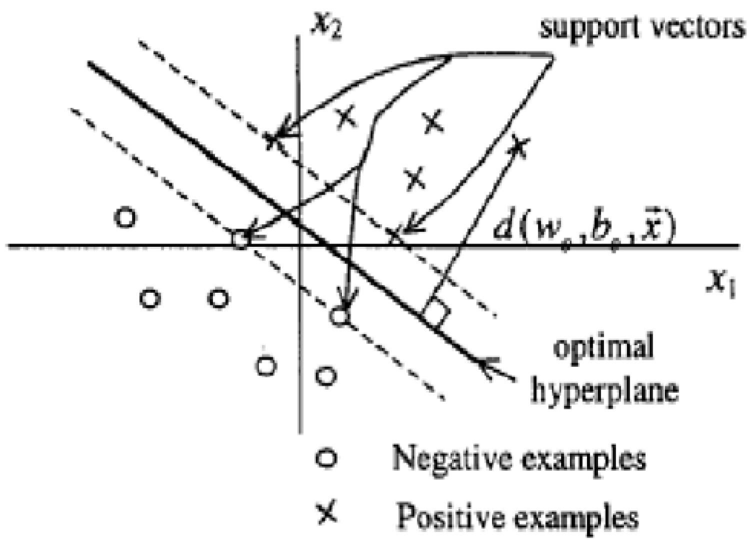


Fig. 5. Support Vector Machine

$$(\vec{x}_i \quad , y_i)_{i=1}^{N}, y_i = +1/-1 \qquad (4)$$

where x_i is an input pattern, e.g., feature vector in image retrieval, for the i^{th} example and y_i is the label. If the two classes are linearly separable, the hyper plane that does
the separation is:

$$w^T \vec{x} + b = 0 \qquad (5)$$

where $\vec{x}$ is an input vector, w is a weight vector, and b is a bias. The goal of a support vector machine is to find the parameter w_0 and b_0 for a optimal hyper plane to maximize the distance between the hyper plane and the closest data point:

$$w_0^T \vec{x} + b_0 \geq 0 \, for y_i = +1 \qquad (6)$$

$$w_0^T \vec{x} + b_0 \leq 0 \, for y_i = -1 \qquad (7)$$

For a given w_0, and b_0, the distance of a point 2 from the optimal hyper plane defined in equation 6 and 7 is:

$$d(w_0, b_0, \vec{x}) = \frac{\left| w_0^T \vec{x} + b_0 \right|}{\left\| w_0 \right\|} \qquad (8)$$

A linear separable example in 2D is illustrated in Figure 4. If the two classes are non-linearly separable, the input vectors' should be nonlinearly mapped to a high dimensional feature space by an inner-product kernel function $K(\vec{x}, \vec{x}_i)$.

An optimal hyper plane is constructed for separating the data in the high-dimensional feature space. This hyperplane is optimal in the sense of being a maximal margin classifier with respect to the training data. The distance from the hyper plane determined by the support vectors can be used to measure how much an example belonging to one class is different from the other class. This motivates us to use SVM for automatically generating preference weights for relevant images.

III. Comparison Of RF Methods

Bayesian Network is good for understand, but it is not used for fast access images.

In Nearest neighbor search method, data are compressed. So some time, images may be lost their features.

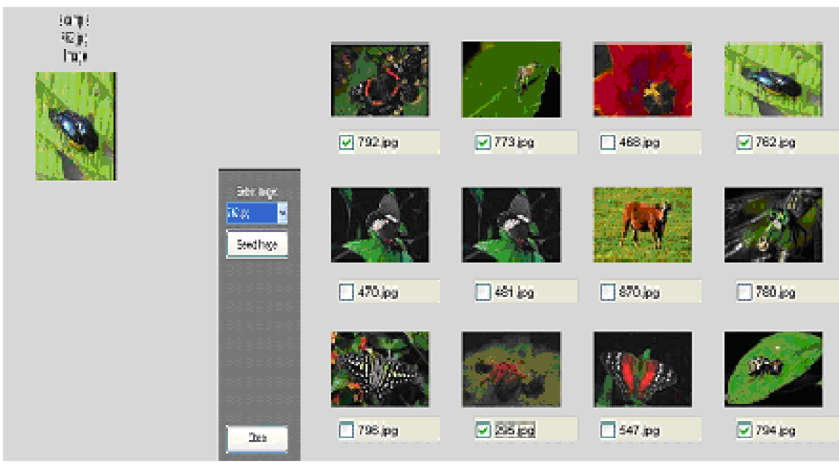
Log based Relevance Feedback method is good for results, but we have to use development algorithm for finding of soft label learning. For that, we have to use soft label support vector machine.

Support Vector Machine is worked on structure risk minimization by minimizing of VC dimensions. It treat the relevance feedback as a strict binary classification by using of maximize the geometric margin and minimize classification error.

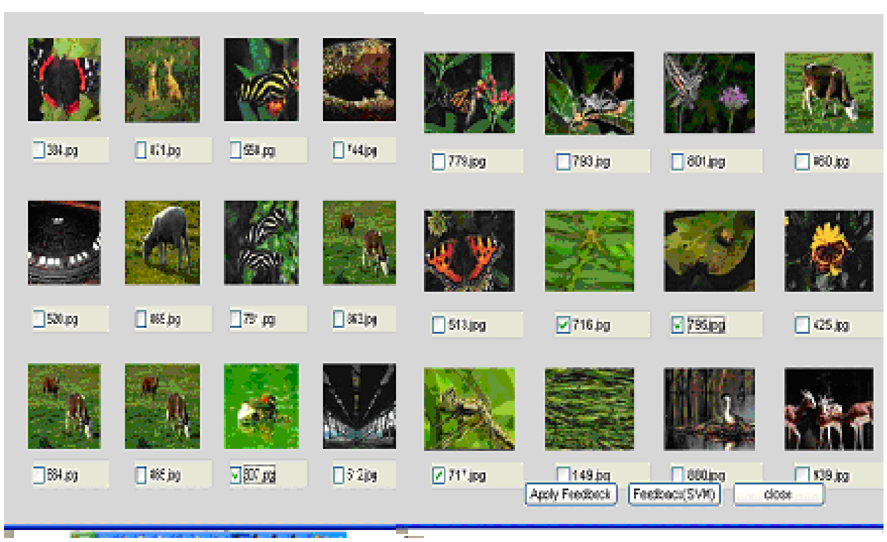
So SVM is best method to use relevance feedback to retrieve images.

IV. Results

Using of MATLAB 7.0, PostgreSQL as database, SVM toolbox, the results as below:

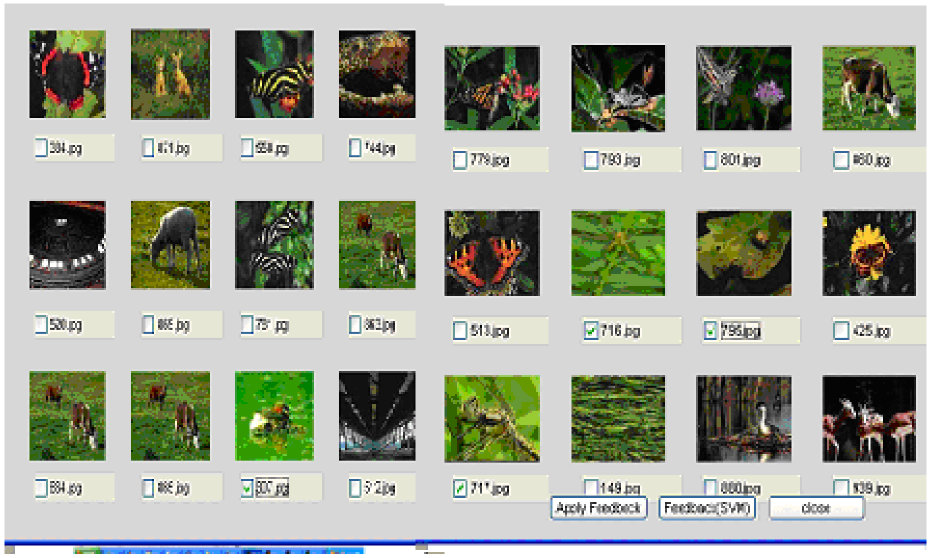


6(a)

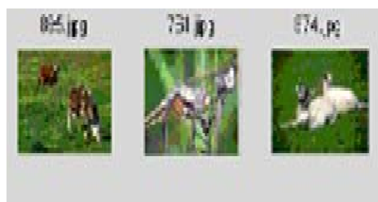


6(b)

Fig. 6(a) and 6(b). Content Based Image Retrieval



7(a)



7(b)

Fig. 7(a) and 7(b). Images are retrieved by Relevance Feedback using of SVM

Survey of 25 users, Relevance Feedback result using SVM's efficiency is 78.6%, which is much better than simple images are retrieved(51.3%).

V. Conclusion

Survey of different methods of Relevance feedback, SVM is best method because of structure risk minimization. Using of SVM, we Using of relevance feedback with SVM, results are more efficient as user perception. SVM classification can be even better if the feature vector used in more relevant to images.

User	Example Image	Feature based image retrieve	Relevance Feedback Images using SVM	Total relevant images as example images
User1	107.jpg	10(33.33%)	21(70.0%)	30
User2	100.jpg	9(47.36%)	15(78.94%)	19
User3	441.jpg	7(20.58%)	22(64.7%)	34
User4	119.jpg	5(38.46%)	12(92.30%)	13
User5	464.jpg	10(50%)	15(75%)	20
User6	762.jpg	7(41.17%)	14(82.35%)	17
User7	Brick_1.jpg	11(84.6%)	12(92.3%)	13
User8	Water_6.jpg	5(41.66%)	11(91.66%)	12
User9	100.jpg	17(37.7%)	23(51.11%)	45
User10	100.jpg	7(70%)	8(80%)	10
User11	100.jpg	12(80%)	13(86.66%)	15
User12	100.jpg	5(62.5%)	6(75%)	8
User13	100.jpg	7(31.8%)	19(86.36%)	22
User14	107.jpg	6(50%)	9(75%)	12
User15	107.jpg	21(52.5%)	35(87.5%)	40
User16	107.jpg	15(57.69%)	22(86.41%)	26
User17	107.jpg	3(42.85%)	5(71.42%)	7
User18	107.jpg	9(60%)	12(80%)	15
User19	107.jpg	3(30%)	7(70%)	10
User20	107.jpg	6(30%)	15(75%)	20
User21	107.jpg	9(30%)	25(83.33%)	30
User22	100.jpg	9(47.36%)	13(68.42%)	19
User23	107.jpg	11(36.67%)	25(83.33%)	30
User24	107.jpg	10(33.33%)	27(90%)	30
User25	100.jpg	5(30%)	11(73.33%)	15
Average		51.23%	78.60%	

Fig. 8. Average efficiency of Relevance feedback using SVM

ACKNOWLEDGMENT

I would like to give my special thanks to Prof. Swati Jain, Department of Computer Engineering, Institute of Technology, Nirma University for guiding throughout this major project part and providing feedback to improve my work. I heartily thankful to her for her time to time suggestion and clarity of concepts of topic that helped me a lot during this study and implementation.

REFERENCES

[1] P. L. Stanchev and D. G. Jr, “Current state and research trend in the image database systems,” mathematics and education in Mathematics, Brovoez, pp. 66–76, 2002.

[2] D. F. Long, D. H. Zhang, and P. D. D. Feng, “Fundametal of content based image retrieval,” reserch microsoft, 2003.

[3] S. Jain and S.N.Pradhan, “Enhancement of color image retrieval capabilitites: function of color with texture(optimized),” NUCON 2007,Nirma University, December 2007.

[4] I. Valova and B. Rache, “Retrieval by color features in image databases,” International Conference on Computer Systems and Technologies - CompSysTech2002, 2002.

[5] I. Valova and B. Rachev, “Image databases an approach for image segmentation and color reduction analysis and synthesis,” International Conference on Computer Systems and Technologies - CompSysTech2003, 2003.

[6] I. Valova, B. Rachev, and M. Vassilakopoulos, “Optimization of the algorithm for image retrieval by color features,” International Conference on Computer Systems and Technologies - CompSysTech, 2006.

[7] R. M. Hralick, “Statistical and structural approaches to texture,” IEEE .67, p. 786805, 1979.

[8] M. Amadasun and R. King, "Texural features corresponding to texural properties," IEEE Transaction on system, Man and Cybernatics, 1989.
[9] S. C. Hoi, M. R. Lyu, and R. Jin, "A unified log-based relevance feedback scheme for image retrieval," IEEE Transaction on knowledge and data engineering, Vol. 18, No. 4,, April 2006.
[10] Tesic.J. and M. B, "Nearest neighbor search for relevance feedback. in computer vision and pattern recognition," IEEE Computer Society Conference, Volume 2,pp. 18–20, June 2003.
[11] J. Xin and J. S.Jin, "Relevance feedback for content-based image retrieval using bayesian network," conference of research and practice in IT(2004), Vol 36, 2004.
[12] C.-H. Hoi and L. M.R, "Group-based relevance feedback with support vector machine ensembles," ICPR 2004, 17th International Conference on Volume 3, pp. 874 – 877, August 2004.
[13] C.-H. Hoi, C.-H. Chan, and K. Huang, "Biased support vector machine for relevance feedback in image retrieval," 2004 IEEE International Joint Conference on Volume 4, pp. 3189 – 3194, July 2004.
[14] T. Q., H. P., and H. T.S, "Update relevant image weights for content-based image retrieval using support vector machines," 2000 IEEE International Conference on volume 2, 2002.
[15] D. Zhang, A. Wong, M. Indrawan, and G. Lu, "Content-based image retrieval using gabor texture features," IEEE Transactions PAMI, 2002.
[16] H. Muller, W. Muller, D. M. Squire, S. Marchand-Maillet, and T. Pun, "Strategies for positive and negative relevance feedback in image retrieval," Swiss National Foundation for Scientific Research, 2002.
[17] V. Franc and V. Hlavac, "Multi-class support vector machine," ICPR, 002. http://www.isis.ecs.soton.ac.uk/resources/svminfo/, Multi-class Support Vector Machine Toolbox.
[18] O. T. and M. H. Y. S., "Relevance feedback document retrieval using support vector machines," 2004 IEEE International Joint Conference on Volume 4, pp. 1359– 1364, July 2004.

Darshana Mistry(ISTE-LM'10). She become a life member ship of ISTE in 2010. Her date of birth is 1st May 1981 in Bharuch. She completed H.S.C from G.S.E.B(Gujarat) in 1998 with 83.67%, B.E.Computer Engineer from S.P.University(V.V.Nagar,Gujarat) with 5.78 CPI in 2002, M.Tech(CSE) from Nirma University(Ahmedabad,Gujarat) with 7.31 CPI in 2009.

She is working as **Coordinator of CE dept., Asst. Professor in Gandhinagar Institute of Technology college, Gandhinagar.** She has 6.8 years experience. She published 1 state level(Gandhinagar, Gujarat, GIT journal,2010), 1national level(Ahmedabad,Gujarat, NUCONE-09-Nirma University,2009), 1 International level paper(V.V.Nagar,Gujarat, ICSSA-09,GCET,2009), I in Internation Journal of Computer Science and Engineering in Volume II, Issue-IV,2905-2909, December 2010.