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A Survey of Semantic Content Based Image Retrieval Techniques using Cloud Computing

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Abstract— The bottleneck of current Content Based Image Retrieval (CBIR) systems is the semantic gap between low level image features and high level concepts. In order to overcome this bottleneck, the most of the recent research work in CBIR is focused on reduction of semantic gap between user and system. This paper presents a comprehensive survey on various methods proposed in literature for the Semantic CBIR. The state of the art techniques available in the literature are divided into three categories: Relevance Feedback Techniques to integrate user's perception, Machine Learning Techniques to associate low level features with high level concepts and Machine Learning using neural network. All above technique requires huge amount of computational power, which may not be available with user device. This becomes a major challenge for semantic CBIR. In order to overcome this challenge, we propose to use cloud computing as distributed computing environment.

Keywords— CBIR, Machine Learning, SVM, Relevance Feedback, Semantic CBIR, Cloud Computing

I. INTRODUCTION

THE rapid development of multimedia and communication technology has led to increased demands for multimedia information, and large collections of images and videos are available to the public. Efficient image and video retrieval tools are required to handle such a large database. The efficient image retrieval and classification tools are required by users from various domains such as remote sensing, medicine, crime prevention etc. Thus the need of efficient image retrieval tools to retrieve the images from large database is becoming a crucial part of the today cutting edge technology.

In text keyword based approach first the images are manually annotated by a set of keywords, and then using these keywords the image retrieval is performed. There are two disadvantages with text based approach. The first is that the manual keyword annotation process takes too much time. The second is annotation inaccuracy due to human perception subjectivity varies from person to person. To overcome these disadvantages of text keyword based approach, content based image retrieval (CBIR) was introduced in early 1980s. In CBIR systems, images are indexed by their visual content such as color, texture, and shape in the form of feature vectors instead of a set of keywords. Some earlier developed CBIR systems are QBIC [2], Photobook [3], and Virage [4], which represents image contents as a function of attributes of image, like color, texture and shape. In such systems the retrieval is performed by comparing the set of features of a query image with the set of features of the images in the database.

The CBIR systems which use only low level features for image retrieval can be considered as the computer centric systems. The performance of such system is not that much satisfactory because of two basic problems:

- The semantic gap
- The human perception subjectivity

The semantic gap is because of differce between the information that one can extract from the visual data and the interpretation in a real word situation [5]. Humans tend to use high-level features called concepts like keywords to understand contents of the images and to measure their similarity between
them. While the features extracted from image using image processing techniques are mostly low-level features like color, texture, shape etc. There is no direct mapping between the high-level features and the low-level features, which creates the gap between the features used by the humans and the computer system. Thus even though there is much research efforts on the development of the CBIR systems, the performance of CBIR systems is still inadequate because of the mismatch between the user semantic concepts and system generated low level image features. The second one is the human perception subjectivity. The human perception may vary from person to person. Different persons, or the same persons under the different circumstances, may perceive the same image differently.In order to conquer these problems, image retrieval systems should be aimed to support high-level querying and browsing. Most of the early stage research on CBIR was focused on the finding the best image feature representations. A comprehensive Survey on CBIR can be found in [6]-[7]. Liu [et.al] [8] presented a detailed survey on various methods for reduction of semantic gap in CBIR.

II. RELEVANCE FEEDBACK TECHNIQUES

The step by step and automatic refinement of a query is known as relevance feedback technique in information retrieval and was first used in text based information retrieval [9]. In the past 30 years, relevance feedback (RF) has been an effective query modification approach for improving the performance of information retrieval (IR). Relevance Feedback (RF) methods are applied to CBIR in early 1990s to integrate users perceptions in retrieval system and to reduce the gap between high level image concepts and low-level image features. Relevance feedback can be seen as a type of supervised learning to adjust the queries using the the users feedback. In implementing relevance feedback in a CBIR system, minimum requirements need to be fulfilled by the retrieval system [10].

- The system must show the initial results to user, based on predefined similarity metrics.
- The user must indicate which images are relevant to the current query image and which images are not relevant.
- The system must change its mechanism depends on images included in the positive and negative feedback.

  The main idea of relevance feedback technique is for the system to understand the users information needs and returns refined results [10].

Query shifting aims to moving the query towards the region of the features containing the set of relevant images and away from the region of the set of non-relevant images [9]-[13]. Feature relevance weighting techniques are based on a weighted similarity metric where relevance feedback information is used to update the weights associated with each feature in order to model users need [14] - [17]. The Bayesian method [18]- [20] estimates the probability of a database image being relevant to the query and updates it with iteration [9]. This approach is theoretically sound as it does not rely on the nearest-neighbor search. Some systems incorporated combination of these techniques [20] - [23].

A. Relevance Feedback Using Query Point Movement

Query shifting mechanisms seems to be more useful when the first retrieval contains few relevant images. In this case the user may have queried the database using an image sample located near the boundary of the relevant region in the feature space. More relevant images can then be retrieved by moving the query away from the region of non-relevant images towards the region of relevant images. A procedure belonging to the query point movement was proposed by Ciocca and Schettini [11], who present a very simple algorithm for computing a new query point Q that can better represent the images of interest to the user. The procedure takes the set of relevant images, the user has selected and computes a new point based on the standard deviation of the features used.

A different perspective has been followed in [9], where the relevance feedback based on Bayesian decision theory is presented. In this a Bayesian decision theory is used to compute the new query point based on the relevance feedback provided by the user. The basic idea in this approach is to find the decision boundary between relevant and non-relevant images in the neighbourhood at the old query, and the fresh query is then placed near boundary, on the side containing the relevant images.

In relevance feedback due to practical considerations it is not feasible to burden the user with marking a large number of objects as relevant or non-relevant. To tackle this problem Wichterich [et al] [12], proposed a technique to utilize the history of all objects that the user selected throughout the entire Relevance Feedback procedure to reshape the query region. They provided an efficient method for calculating such a history-shaped region. Using the same mathematical framework, they are able to seamlessly extend the Relevance Feedback system to recognize that a Relevance Feedback session commonly exhibits two phases:

- Exploring the database to find a good query point
- Deciding on the ranking as seen from that query point via shaping the query region to match the correlation of features that best describes the users preferences.

  In [13], Traina [et.al.] discussed two novel relevance feedback techniques called RF Projection and RF using Multiple Query Centre, which integrate a new way to implement the query centre movement with a suitable weighting on the similarity function. According to the authors these techniques when integrated to a CBIR system, improves the precision of the results using texture features up to 42%, and employing at most 5 iterations.

B. Relevance Feedback Using Feature Re-weighting

When the query is able to retrieve large number of relevant images, then it is more effective to refine the result by some feature re-weighting mechanism than moving the query point [24]. Feature relevance weighting techniques are based on a weighted similarity metric where relevance feedback by user is used to update the weights associated with each feature in order to refine results [10]. Rui [et.al] [14] proposed an interactive retrieval approach which takes into account the users high level query and perception subjectivity by dynamically updating certain weights. The system uses relevance feedback to update queries so as to place more weight on relevant elements and less on irrelevant ones.

Most of the techniques found in literature perform relevance feedback on only low-level image features and so fails to address the images semantic content. In [15], Lu [et al] proposed a relevance feedback framework taking use of both the image high level semantic (keyword) and the low level features. By forming a semantic network on top of the keyword association on the images, they are able to accurately deduce and utilize the images semantic contents for retrieval purposes. They have also presented the system Find based on the proposed framework for the retrieval of images from

World Wide Web. This system supports three types of retrieval i.e. retrieval based on the keywords, retrieval by examples and browsing the entire image database using a predefined category hierarchy.

In [16], Yu [et.al.] proposed a novel interactive boosting framework to integrate user feedback about results into boosting scheme and bridge the gap between high-level concept and low-level image features. According to authors their method achieves more performance improvement by introducing the relevance feedback in boosting scheme than traditional boosting algorithms because human judgment is accumulated iteratively to facilitate learning process.

In [17] a new method for combining the visual and semantic features in image retrieval is discussed. To improve the performance of CBIR, first they used Fuzzy K-NN classifier to assign the initial labels to the database images and these labels are then gradually modified by relevance feedback from the user.

C. Relevance Feedback using Probabilistic Approach

The Bayesian method estimates the probability of a database image being relevant to the query and updates it with iteration [9]. Bayesian learning requires less number of training samples as compared to other learning techniques. In [18], Gaussian mixture model (GMM) is applied to represent the distribution of positive images in relevance feedback. They have proposed a novel method to estimate the parameters of GMM using positive and negative examples marked by the user. To handle the problem of few training samples they incorporated the unlabeled images along with the labelled (relevant or non relevant) images to estimate the co-variance matrices of GMM. According to authors, their GMM-based RF method outperforms than single Gaussian model. Many of the relevance feedback systems assume that the user is consistent when specifing feedback. In reality, user consistency is hard to achieve. To overcome this limitation which ignore the inconsistent characteristics of human feedback, Xin and Jim [19], proposed a relevance feedback algorithm which keeps track of user feedback inconsistency.

They used Gaussian mixture model to represent the users target distribution. The long-term feedback learning with real semantics extraction is discussed in [20]. In this paper Jiang [et.al.] proposed a Multi-layer Semantic Representation (MSR) for image database and an algorithm is implemented to automatically build the MSR through long- term relevance feedback learning process. The MSR memorizes the multi-correlation among the images and extract the hidden concepts distributed in multiple semantic layers from these memories. One semantic layer corresponds to one kind of hard partition of semantic space. Concepts without intersection between each other are put into one semantic layer, and concepts with intersection are put into different layers. They also proposed an integrated algorithm to seamlessly combine the semantic information provided by accumulated MSR with the short-term learner to help retrieval in subsequent query sessions. Their experimental results show that the proposed system can describe the real world semantic concepts effectively.

Wang [et.al.] [21] proposed a model iSearch to improve the query accuracy and the efficiency of CBIR system. This model is based on two ideas first; retrieval history of past users is used as guide for returning the initial set of result. The Second is to use EM algorithm to model the users target distribution within a transformed feature space. In the retrieval process when a query is submitted to the system, feedback process module would check whether there are common patterns for different users on this query. If such patterns exist, some image candidates will be obtained by using these patterns. The feature space will then be transformed based on these candidates to make relevant images closer and EM algorithm will then be used to simulate the distribution of the new feature space by a mixture of the Gaussian distribution.

Most of the classification techniques treat the relevance feedback problem as a binary classification problem and often they do not consider the imbalanced dataset problem, which means that the numbers of irrelevant images are significantly larger than the number of relevant images for each query. This imbalanced dataset problem would lead the positive data (relevant images) to be overwhelmed by the negative data (irrelevant images). In order to tackle the problem of imbalanced dataset in CBIR, Peng & King [22] proposed to use a modified MPM, called biased minimax probability machine (BMPM) which models the relevance feedback problem better and reduce the errors caused by the imbalanced dataset problem. According to authors the BMPM model has better performance compared to other methods presented in the literature to tackle the problem of imbalanced dataset problem.

Some systems incorporated using combination of these techniques [23], [24]. Li & Yuan [23], proposed a novel method by combining the two strategies in relevance feedback i.e. Query point movement & Feature relevance weighting. The method proposed in [23] can accelerate the convergence speed by updating vectors and their weights at same time. The experimental results shown that method achieves high accuracy and effectiveness in image retrieval [23].

III. MACHINE LEARNING TECHNIQUES FOR CBIR

Most of the recent works on content based image retrieval uses machine learning as an important tool to handle the semantic gap problem. Machine learning tool uses the supervised or unsupervised machine learning techniques to derive high level semantic features. The goal of supervised learning is to predict the value of an outcome measure (for example, semantic class label) based on a training set. The purpose of unsupervised learning is to find the natural partitions in the dataset that is to find the regularities in the input.

A. Supervised Learning

In supervised learning techniques an image semantic classifier is derived through learning and training a set of prelabelled sample images to categorize or tag the new images with suitable semantic labels. Image classification has often been treated as a pre-processing step for speeding up image retrieval in large databases and improving accuracy, or for performing automatic image annotation. Support vector machine (SVM) [25] and Bayesian classifier are often used to learn high-level concepts from low-level image features.

Support Vector Machine is considered as one of the best technique for pattern classification and non-linear regression introduced in 1992 by Boser [et.al.], [24]. The goal of SVM is to produce a mechanism which predicts the target values (class labels) of the test data, based on the training data. Their main idea is to construct a hyperplane that acts as a decision space in such a way that the margin of separation between positive region and negative region examples is maximized [26].

In [27], Tian [et.al.], a novel approach is presented using Support Vector Machine (SVM) to automatically update relevant image weights during relevance feedback process. The SVM learning results are used to modify the feature weights for relevant images. Both positive and negative images are used but the priorities are given to the positive feedbacks that have larger distances to the hyper plane determined by the support vectors. Thus the burden on user, to update the weights manually is removed completely. YaLi Qi [28], used SVM to learn the texture feature of the images. In this mechanism after the initial retrieval using texture histogram, the user provides his feedback as relevant or non-relevant. Using feedback the SVM is then trained to further refine the retrieval results. According to authors the texture histogram is more advantageous as it pays more attention on salient changes of pixels intensities and which is more consistent with human vision perception for image texture.

In image retrieval, the images labelled by the user are usually very limited in number, which is called as the sample problem in image retrieval. This problem is handled by Wang [et.al] [29] by bootstrapping SVM active learning using labelled and randomly selected un-labelled images from the database. Thus the learning and retrieval efficiency is improved without putting the burden on user to label the images in the database. A two stage mapping model using Support Vector Machine for assigning the semantic keywords to images is discussed in [30] by Tsai [et.al.]. In the first stage of this model SVM classifiers are used to classify the color and texture feature vectors of image regions into their feature level concepts. These concepts are then given as input to second stage mapping. In the second stage a fuzzy inference system is used for making decisions and assigning keywords to the segmented regions to describe the main concept of the image.

A content based semantic indexing of images using Fuzzy Support Vector Machine (FSVM) is proposed in [31] by Li [et.al.]. Their method of semantic indexing is divided into three steps i) feature extraction ii) Concept modeling and iii) Semantic indexing. For feature extraction they have defined a weighted 3-level pyramid for each image and for each level of the pyramid color, texture and edge histogram are extracted. In concept modeling the image meta-data is then converted

into numerical value. This numerical dataset is then trained into concept model using FSVM, and all the concept models are stored into the libraries along with its description. In the indexing process first the features of the query image are extracted and the image is compared statically with the concepts stored in library and the likelihood of the image with each concept is determined. The concept with likelihood greater than the threshold value will be used to annotate the images. Here the description of the concept in the form of linguistic terms will be associated with the image.

Semantic classification of home photo using SVM as concept detector is presented in [32] by yang [et.al.]. To reduce the semantic gap they used local concept detector to detect the semantic meaning of local regions of image. The concept merging is applied to compensate the classification error due to image localization with a fixed block size. These merged concepts represent the local photo concepts, which are then given as input to the global concept detectors. The global concept represents the higher level of semantics than the local semantics. Based on the output from the global concept detector the whole image is categorized into multiple semantic categories.

A SVM using kernel based on fuzzy basis function is presented in [33]. In their approach the semantic information is extracted in the form of linguistic fuzzy rules. The proposed system is effectively used for the image classification. An image semantic classification approach based on kernel PCA SVM is proposed in [34]. A region based image retrieval using graph kernel based support vector machine (SVM) is presented [35]. In this approach Salient Region Adjacency Graph (SRAG) are used to represent the image semantics. First the salient regions are extracted from the images and using these salient regions Salient Region Adjacency Graphs (SRAGs) are constructed. These SRAGs are then used to train the SVM, which are then used for the image retrieval and shown the effective results than traditional SVM.

The Bayesian framework is a probabilistic method to combine information gathered from multiple sources [36]. Nguyen [et.al] used Bayesian learning to integrate the regional andglobal features for image categorization. In their approach the regional features are used to learn the mid level concepts within an image and global features are used to learn the image category. Then these mid level concepts and image category labels are reconciled using the Bayesian network.

The Bayesian classifier then classifies the images using object ontology which describe the relation between mid level concept and image category.

B. Unsupervised Learning

Image clustering is a typical unsupervised learning technique used to describe the high-level concepts within the images. Clustering groups the images into different groups, such that the images in each group share the similarity trends and patterns and images between the clusters are very dissimilar to each other. The purpose of clustering is to reduce the search space for the retrieval [37]. The K-means and normalized-cut (N-cut) are widely used clustering algorithms in the literature.

Han et.al [38], proposed a memorization learning model. First they build an image link network to reflect the semantic relationship among images in a database using the user provided relevance feedback. In this network, there is a directionless link between two images if both of them are relevant to the same query in a search session, and the link intensity reflects the semantic correlation between them. Then k-means algorithm is adapted to group images into a few semantically correlated clusters. Each image cluster could be considered to linked to a specific semantic concept and they used the rank of an image to describe how likely the image contains the specific semantic concept. Next, hidden semantic concept similarity between two images is estimated using these clusters. Finally, the semantic concept similarity between two images is calculated by combining their link intensity and hidden semantic similarity.

Unsupervised clustering using color and texture is proposed in [39] by Maheshwari [et.al]. They used color moments and Gabor filters to extract the color and texture features of the images respectively. These extracted features are then applied in clustering algorithm. The author used two clustering technique as K-means clustering and Hierarchical clustering. They showed that k-means algorithm performs better than hierarchical clustering. Chen [et.al] [40], introduced a novel image retrieval scheme, CLUster-based rEtrieval of images by unsupervised learning (CLUE). CLUE is built on a hypothesis that images on the same semantics tend to be clustered. Most of the existing clustering techniques consider image as a whole to form the various clusters. However, in most of the cases a users interest is often just one part of the image i.e. a region in the image that has an obvious semantic meaning. Therefore, rather than viewing each image as a whole, it is more reasonable to view it as a set of semantic regions. Such region based image clustering is presented by Liu [et.al.] in [41].

A framework using both supervised as well as unsupervised learning based techniques to associate MPEG-7 based color and edge features of images with their high-level semantic concepts is presented in [42] by Bhattacharya [et.al.]. It represents images in a level of information abstraction based on confidence or membership scores obtained from supervised as well as unsupervised learning algorithms. They also presented the fusion-based similarity matching function to rank and retrieve most similar images compared to a query image.

IV. MACHINE LEARNING USING NEURAL NETWORK FOR CBIR

Beside to supervised and unsupervised learning methods Neural Network is also used for learning and image classifications. Recently the Neural Network has shown a powerful tool for pattern recognition in a variety of applications. The use of neural nets for the feature extraction or selection seems promising, since the ability to solve a task with a lesser number of the resources is included in the training of the network [43].

Li [et.al] [44], Presented a neural network approach for semantic based retrieval using linguistic expression based image description framework (LEBID). They have used linguistic variable to represent the texture semantics using Tamura texture model. The authors claim that their approach has the potential to reduce the semantic gap. A non-linear relationship between low-level features and high level features is discussed by Sadek [et.al.] [45] using SNNIR (Splines Neural Network based Image Retrieval). They used color features in the form of color coherence (CC) vector and color moment for the image retrieval. In the retrieval process these two features are given as input to the splines neural network which predicts the metric vectors of the query image and database image. These two metric vectors are then used to calculate the similarity between the two images using
cosine similarity function.

A semantic based image retrieval using two-phase fuzzy art neural network is presented in [46] by Chang [et.al.]. They used PCA to extract the significant image features to describe the eight high-level semantic items. These features are then applied to two-phase Fuzzy Adaptive Resonance Theory Neural Network (FUZZY-ARTNN) for image classification. An intelligent image characterization through neural learning is presented in [47]. In the retrieval process, when the query image is submitted to model, it will pass through the low level feature extraction. These low-level feature vectors are given as input to neural network, which creates a high level vector. This vector is then compared with the database image vector using a distance function. Then the images with shortest distance will be ranked and presented to the user.

V. CLOUD COMPUTING

Cloud computing is defined as “A large-scale distributed computing paradigm that is driven by economies of scale, in which a pool of abstracted, virtualized, dynamically-scalable, managed computing power, storage, platforms, and services are delivered on demand to external customers over the Internet.” [47] Cloud computing is a model for enabling convenient, on demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction[48]. Major problem with semantic CBIR is computing time required for extracting features from image. This results into slowdown of CBIR system. This problem can be solved using cloud computing.

VI. CONCLUSION

From this survey it has been recognized that reduction of semantic gap is still an open research problem mainly, because of the computer’s image understanding incapability. Finding the semantic meaning using low level features and map it to the high level features is still an unsolved problem. A CBIR system that can understand images and provides semantic based image retrieval can be developed using neural network to overcome the semantic gap problem. In real application this will require huge amount of computing power, which normal users may not have. This problem can be solved with implementation of semantic CBIR using cloud computing model.

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REFERENCES

[1] A. Lakdashti, M. Moin, and K. Badie, Semantic Based Image Retrieval: A Fuzzy Modeling Approach,IEEE/ACS International conference on Computer Systems and Applications (AICCSA), pp.575-581, 2008.

[2] C. Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic, and W. Equitz, Efficient and effective querying by image content, J. Intell. Inf. Syst. 3 (34), pp.231 262, 1994.

[3] A. Pentland, R.W. Picard, and S. Scaroff, Photobook: content-based manipulation for image databases, Int. J. Comput. Vision 18 (3), pp.233- 254, 1996.

[4] A. Gupta and R. Jain, Visual information retrieval, Commun. ACM, vol. 40, no.5, pp.70-79, 1997.

[5] A. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, Content-Based Image Retrieval at the End of the Early Years, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, No. 12, pp. 1349- 1380, Dec. 2000.

[6] M. Kokare, B. N. Chatterji, and P. K. Biswas, A survey on current content based image retrieval methods, IETE Journal of Research, vol. 48, nos. 3 & 4, pp. 261-271, May-Aug 2002.

[7] M. Oussalah, Content Based Image Retrieval: Review of State of Art and Future Directions first workshop on Image Processing Theory, Tools & Applications, pp. 1-10, 2008. [8] Y. Liu, D. Zhang, G. Lu, and W. Ma, A survey of content-based image retrieval with high-level semantics, Pattern Recognition 40, pp.262 282, 2007.

[9] G. Giacinto, and F. Roli, Bayesian relevance feedback for content-based image retrieval, Pattern Recognition society 37, pp.14991508, Elsevier 2004.

[10] Z. Shoaie and S. Jjinni, Semantic image retrieval using relevance feedback and reinforcement learning algorithm, 5th Int. Symposium on I/O Communication and Mobile Computing, pp. 1-4, 2010.

[11] G. Ciocca and R. Schettini, A relevance feedback mechanism for content based image retrieval,Journal of Information Processing and Management, vol. 35 (1), pp. 605 632, 1999.

[12] M. Wichterich, C. Beecks, and T. Seidl, Ranking Multimedia Databases via Relevance Feedback with History and Foresight Support, ICDE Workshop 2008, pp.596-599, 2008.

[13] Agma Traina, J. Marques, and C. Traina, Fighting the Semantic Gap on CBIR Systems through New Relevance Feedback Techniques,in Proc. of the 19th IEEE Symposium on Computer-Based Medical Systems (CBMS'06), pp. 881-886, 2006.

[14] Y. Rui, T. S. Huang, M. Ortega, and S. Mehrotra,Relevance Feedback: A Power Tool for Interactive Content-Based Image Retrieval, IEEE Transaction On Circuits and Systems For Video Technology, Vol. 8, No. 5, pp.644-655, Sept. 1998.

[15] Y. Lu, H. Zhang, L. Wenyin, and C. Hu, Joint Semantics and Feature Based Image Retrieval Using Relevance Feedback,IEEE Transactions on Multimedia, Vol. 5, No. 3, pp. 339-347, Sept. 2003.

[16] J. Yu, Y. Lu, Y. Xu, N. Sebe, and Q. Tian,Integrating Relevance Feedback In Boosting For Content-Based Image Retrieval, in ICASSP- 2007, Vol. 1, pp.I-965 - I-968, 2007.

[17] H. Nezamabadi-pour and E. Kabir, Concept learning by fuzzy k-NN classification and relevance feedback for efficient image retrieval, Expert Systems with Applications 36, pp.5948 5954, Elsevier 2009.

[18] F. Quain, M. Li, L. Zhang, H. Zhang, and B. Zhang,Gaussian Mixture Model For Relevance Feedback In Image Retrieval, in Proc. of Inter. Conference on Multimedia and expo, Vol. 1, pp. 229-232, 2002.

[19] J. Xin and J. Jin,Learning from User Feedback for Image Retrieval, in proc. of ICES-PCM 2003, Vol. 3, pp.1792-1795, Dec. 2003.

[20] W. Jiang, G. Er and Q. Dai, Multi-layer Semantic Representation Learning For Image Retrieval, International Conference on image Processing (ICIP), Vol. 4, pp.2215-2218, 2004.

[21] H. Wang, B. c. Ooi, and A. K .H. Tung, SEARCH: Mining Retrieval History for Content-Based Image Retrieval, in Proceedings of the Eighth International Conference on Database Systems for Advanced Applications (DASFAA 03), pp.275-282, 2003.

[22] X. Peng and I. King, A biased minimax probability machine-based scheme for relevance feedback in image retrieval, Neurocomputing, 72, pp.20462051, Elsevier 2009.

[23] B. Li and S. Yuan, A Novel Relevance Feedback Method in Content- Based Image Retrieval, in Proceedings of the International Conference on Information Technology: Coding and Computing (ITCC04), Vol. 2, pp. 120-123, 2004.

[24] G. Giacinto, F. Roli and G. Fumera, Comparison and Combination of Adaptive Query Shifting and Feature Relevance Learning for Content-Based Image Retrieval, in Proc. of 11th Inter. Conference on Image Analysis and Processing, pp.422-427, 2001.

[25] B. Boser, I. Guyon, and V. Vapnik, A training algorithm for optimal margin classifiers, 5th Annual ACM Workshop on COLT, pp. 144 -152, 1992.

[26] V. Vapnik. Statistical Learning Theory. Wiley, 1998. [27] Q. Tian, P. Hong, and T. Huang, Update Relevant Image Weights for Content-Based Image Retrieval Using Support Vector Machines, Inter. Conference on Multimedia and Expo (ICME), vol.2, pp.1199-1202, 2000.

[28] Y. Qi, Relevance Feedback Based on Texture Histogram and SVM, Int. Workshop on Intelligent Systems and Applications, pp. 1-4, 2009.

[29] L. Wang, K. Chan, and Z. Zhang, Bootstrapping SVM Active Learning by Incorporating Unlabelled Images for Image Retrieval, in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 03), vol.1, pp. I-629- I-634, 2003.

[30] C. Tsai, K. McGarry, and J. Tait,Using Neuro-Fuzzy Techniques Based on a Two-Stage Mapping Model for Concept-Based Image Database Indexing, Proceedings of the IEEE Fifth International Symposium on Multimedia Software Engineering (ISMSE 03), pp. 6-12, 2003

[31] J. Li, S. Huang, R. He, and K. Qian, Content-based Semantic Indexing of Image Using Fuzzy Support Vector Machines, Chinese conference on pattern recognition, pp.1-6, 2008.

[32] S. Yang, S. Kim, K. Seo, Y. Ro, J. Kim, and Y. Seo, Semantic categorization of digital home photo using photographic region templates, Journal of Information Processing and Management, vol. 43, pp. 503 514, 2007.

[33] E. Spyrou, G. Stamou, Y. Avrithis, and S. Kollias,Fuzzy Support Vector Machines for Image Classification Fusing MPEG-7 Visual Descriptors, 2nd European Workshop on Integration of knowledge, Semantics and digital Media Technology, pp. 23- 30, 2005.

[34] L. Shi, G. Gu, H. Liu, and J. Shen,Image Semantic Classification algorithm Research On Kernel PCA support vector machine, IEEE inter. Symposium on Knowledge Acquisition and modeling Workshop, pp.422- 424, 2008.

[35] R. Zhang, J. Yuan, J. Huang, Y. Wang, and B. Hong, A Novel Generalized SVM Algorithm with Application to Region-based Image Retrieval, International Forum on Information Technology and Applications, vol.2, pp.280-28, 2009.

[36] S. Aksoy, K. Koperski, C. Tusk, G. Marchisio, and J. Tilton, Learning Bayesian Classifiers for Scene Classification With a Visual Grammar, IEEE Transactions On Geoscience and Remote Sensing, Vol. 43, No. 3, pp.581-589, 2005.

[37] Y. Liu, X. Chen, C. Zhang, and A. Sprague,An Interactive Region-Based Image Clustering and Retrieval Platform, ICME, pp.929-932, 2006.

[38] J. Han, M. Liz, H. Zhang, and L. Guo, A Memorization Learning Model For Image Retrieval, in Proc. of Int. Conference on Image processing (ICIP), Vol.3, pp.III-605-III-608, 2003.

[39] M. Maheshwari, S. Silakari, and M. Motwani, Image Clustering using Color and Texture, First Inter. Conference on Computational Intelligence, Communication Systems and Networks, pp.403-408, 2009.

[40] H. Chen, J. Z. Wang, and R. Krovetz, An Unsupervised Learning Approach to Content-Based Image Retrieval, in Proc. of 7th International Symp. on Signal Processing and its Applications, Vol. 1, pp.197-200, 2003.

[41] P. Bhattacharya, M. Rahman, and B.C. Desai,Image Representation and Retrieval Using Support Vector Machine and Fuzzy C-means Clustering Based Semantical Spaces, in Proceedings of the 18th International Conference on Pattern Recognition (ICPR'06), vol.1, pp. 929-935, 2006.

[42] C. Barcelos, E.F. Ribeiro, and M. A. Batista, Image Characterization via Multilayer Neural Networks,20th IEEE International Conference on Tools with Artificial Intelligence, vol.1, pp.325-332, 2008.

[43] Q. Li, Z. Shi, and S. Luo, A Neural Network Approach for Bridging the Semantic Gap in Texture Image Retrieval, in Proceedings of International Joint Conference on Neural Networks, Orlando, Florida, USA, August 12-17, 2007, pp.581-585, 2007.

[44] S. Sadek, A. Al-Hamadi, B. Michaelis, and U. Sayed,Cubic-Splines Neural Network- Based System for Image Retrieval, in proceedings of ICIP, pp.273-276, 2009.

[45] C. Chang, H. Wang, and R. Jian, Semantic Image Retrieval with Fuzzy- ART, Inter. Conference on System Science and Engineering (ICSSE), pp.69-74, 2010.

[46] E. Ribeiro, C. Barcelos, and M.A. Batista, Intelligent Image Characterization, 15th Inter. Conference on Systems, Signals and image Processing, pp. 209-212, 2008.

[47] Foster, Ian, Yong Zhao, Ioan Raicu, and Shiyong Lu. "Cloud computing and grid computing 360-degree compared." In Grid Computing Environments Workshop, 2008. GCE'08, pp. 1-10. IEEE, 2008.

[48] Dillon, Tharam, Chen Wu, and Elizabeth Chang. "Cloud computing: Issues and challenges." In Advanced Information Networking and Applications (AINA), 2010 24th IEEE International Conference on, pp. 27-33. IEEE, 2010

