IRAbMC : Image Recommendation with Absorbing Markov Chain

Sejal D*, Rashmi V*, Dinesh Anvekar**, Venugopal K R*, S S Iyengar*** and L M Patnaik****

*Department of Computer Science and Engineering
University Visvesvaraya College of Engineering, Bangalore University, Bangalore-560001,
**Alpha College of Engineering, Bangalore
***Florida International University, USA
****Indian Institute of Science, Bangalore, India

***Abstract*—Image Recommendation is an important feature for search engine as tremendous amount images are available online. It is necessary to retrieve relevant images to meet user's requirement. In this paper, we present an algorithm Image Recommendation with Absorbing Markov Chain (IRAbMC) to retrieve relevant images for user input query. Images are ranked by calculating keyword relevance probability between annotated keywords from log and keywords of user input query. Absorbing Markov chain is used to calculate keyword relevance. Experiments results show that the IRAbMC algorithm outperforms Markovian Semantic Indexing (MSI) method with improved relevance score of retrieved ranked images.**

Keywords— Annotation based Image Retrieval, Content based Image Retrieval, Image Annotation, Image Recommendation

I INTRODUCTION

With the explosive growth of World Wide Web, billion of images are now available online. The rapid growth of digital images on the Web makes it difficult for the user to find and access images of their interest. Therefore, some additional processing is needed to retrieve relevant images as per the user requirement. An image retrieval system provides an effective way to retrieve a set of images to meet the users' demand.

There are two basic image retrieval techniques: (i) Content based Image Retrieval (CBIR) and (ii) Annotation based Image Retrieval (ABIR). In CBIR technique, images are retrieved based on color, shape and texture features or other information that can be derived from image itself rather than the meta-data such as keywords, tags, or descriptions associated with the image. In CBIR method, a gap exists between low level visual features and high level semantics i.e., user request query. Many CBIR techniques have been developed which make use of relevance feedback in which user progressively refines the search results. But this method is impractical for very large dataset as it requires intensive computation.

In Automatic image annotation method, a computer system automatically assigns meta-data in the form of keywords to images. Images are retrieved using this annotation. In ABIR system, semantic content is incorporated efficiently into t ext-based queries and image captions. Hence, many techniques are developed for automatic image annotation [1]–[4]. In online image retrieval similar to Google image search engine, users submit queries which consist of keywords, to search relevant images of their interest. The search engine returns a list of images. Users can click or ignore the returned images. If users are not satisfied with the retrieved images, they semantically refine the queries. Therefore, the keywords of the queries give brief but comprehensive meaning of users need and can be used to find relevance between annotation and user input query.

Motivation: Existing web image search engines (i.e. Google, Yahoo! Image Search) retrieve images with text-based queries. These text queries are matched with textual information such as tags, comments, surrounding text, titles and URLs along with web images. Currently, only 10% of web images have meaningful description (annotation). Although, search engine retrieves images efficiently, they are only able to deliver around 42% precision and 12% recall [5]. Searches do not find relevant results on Google search for 52 % of 20,000 queries [6]. This is because of two main reasons: (i) queries are in general short and ambiguous, i.e. the query DM has the interpretation of both *Data Mining* and *Data Mart*, and (ii) users may have different intentions for the same query, e.g. for query apple, users with apple product fan have different meaning than users who like apple fruit. Therefore, it is necessary to improve image recommendations results in order to satisfy user's need and usability of search engine.

Contribution: In this work, annotation based image recommendation with Absorbing Markov Chain is presented. Keyword relevance probability is calculated for annotated keywords for all the images. Absorbing Markov chain is incorporated to find relevant link between keywords of input query with annotated keywords. Images are filtered based on their annotation similar to input query keywords. Finally, images are ranked by calculating Markov distance between user input query and annotation related to images. This method gives accurate image recommendations when the per image annotation data is also limited.

Organization: This paper is organized as follows: We have reviewed various Content Based and Annotation Based Image Retrieval techniques under section II. Section III describes Markov Chain and Absorbing Markov Chain methods. Section IV presents Image Recommendation Algorithm.

978-1-4673-6540-6/15/$31.00 ©2015 IEEE

Section V discusses data collection, experiment setup and performance evaluation. Finally, conclusions are presented in section VI.

II RELATED WORK

In this section, we have reviewed different techniques for image retrieval. There are mainly two methods to retrieve images: Content Based Image Retrieval (CBIR) and Annotation Based Image Retrieval (ABIR). In CBIR system, images are retrieved based on low level features and in ABIR images are retrieved by incorporating more efficient semantic content into both text-based queries and image captions.

A. Annotation Based Image Retrieval

Fan et al., [7] have developed a method for multilevel annotations of large-scale images automatically. Pham et al., [8] have studied the effect of Latent Semantic Analysis (LSA) for multimedia document retrieval and automatic image annotation.

Wang et al., [9] have presented a search based annotation approach Arista, which understands the semantics of an image by propagating labels of closely similar images retrieved from a large scale data set. In annotation based image retrieval evolutionary approaches [10]–[12] to annotate images can be used.

Hofmann et al., [13] have proposed an unsupervised learning technique called Probabilistic Latent Semantic Analysis (PLSA) which aims to identify the semantic relations between the words. Zhang et al., [14] have proposed a structural image retrieval method based on automatic image annotation and region based inverted file. Kilinc et al., [15] have introduced an expansion and re-ranking approach for annotation based image retrieval from web pages

B. Content Based Image Retrieval

Rahman et al., [16] have suggested a classification-driven biomedical image retrieval framework. It employs supervised learning techniques for image filtering and similarity fusion for diverse medical images of different modalities. Cheng et al., [17] have proposed a unified relevance feedback framework to support relevance feedback (RF) for web image retrieval. Riad et al., [18] have presented a new majority voting technique to retrieve images with textual and visual feature.

Kekre et al., [19] have discussed Mask-Shape-BTC (Block Truncation Coding) method of image retrieval using shape features. The shape features are extracted using slope magnitude method applied on gradient of images. He. et al., [20] have proposed a semi supervised method called Maximum Margin Projection(MMP) for dimensionality reduction, which focuses on local discriminant analysis for image retrieval. Liu et al., [21] have proposed four target search methods which are able to reach any given target image with fewer iterations in the worst and average cases.

Guo et al., [22] have presented a technique for content-based image retrieval (CBIR) using ordered-dither block truncation coding (ODBTC) to generate image content descriptor. Gao et. al, [23] have developed an interactive approach to filter out the junk images from keyword-based Google Images search results.

III MARKOV CHAIN AND ABSORBING MARKOV CHAIN

A. Markov Chain

The Markov process is a stochastic process in which the next system state depends only on the current system state. It represents the set of states $S=\{s_1,s_2,s_3..s_N\}$ in which if the current state in s_i, then the probability of next state s_j is defined by the probability p_{ij}. These probabilities are called transition probabilities. The one step transition probability matrix of a Markov process with N states is defined as

$$P_{N,N} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,N} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,N} \end{pmatrix}$$

A Markov chain is a discrete-valued Markov process. The equilibrium vector V of a Markov chain can be given by $v.P^{N} \approx V$, where, v is any probability vector. As n approaches infinity, the Markov chain converges to a certain steady-state vector called equilibrium vector of a Markov chain i.e., the equilibrium vector has identical rows of its states of a Markov process.

The transition probability matrix P is iteratively multiplied by itself n times to find steady state probability vector. When the matrix size is large then matrix multiplication is inefficient. Hence, steady state probability vector P^N can be generated by calculating eigenvalues and eigenvectors of matrix P.

The eigenvalues for a given matrix P is calculated by using det(P - λI) = 0, where λ is a eigenvalue of P , I is the identity matrix and det is determinant. In case of Markov matrix, its cell values are positive and sum of every column is 1, then the largest eigenvalue is λ = 1. The eigenvector x for each λ can be solved using (P - λI)x = 0 or Px = λx. The power of eigenvalues are calculated for any n. P^{N} is calculated by using equation 1.

$$P^{N} = \vee \wedge \vee^{-1} \quad (1)$$

Here, $\vee$ is the matrix of eigenvectors, $\wedge$ is the diagonal matrix of eigenvalues raised to power n and $\vee^{-1}$ is the inverse matrix of $\vee$.

B. Absorbing Markov Chain

When a given state is s_i in which $p_{ii} = 1$, then the state s_i is called absorbing state of a Markov chain. This chain is called Absorbing Markov chain, where once we reached to state si, it is impossible to come out of that state, i.e., the state is absorbed [24]. States that are not absorbing are called transient states. Absorbing Markov chain is used to calculate the average time required to reach absorbing state from any non-absorbing (transient) states.

If t and r represents transient and absorbing states respectively then given transition probability matrix P is reordered as in canonical form as

$$P = \begin{array}{c c} & \begin{array}{cc} T_r & Ab_r \end{array} \\ \begin{array}{c} T_r \\ Ab_r \end{array} & \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix} \end{array}$$

Where, I is the r × r identity matrix, 0 is a r × t zero matrix, R is a non-zero t× r matrix representing transition probabilities from transient to absorbing states and Q is a t×t matrix representing transition probabilities from transient to transient states.

The fundamental matrix of an absorbing Markov chain is defined as $N = (I - Q)^{-1}$ and $N = I + Q + Q^2 + \ldots$. The ij[th] entry of N represents the expected number of times that a process reaches transient state si, starting from transient state si.

The absorption probability matrix B is the t × r matrix with entries b_{ii} which represents the probability that an absorbing chain is absorbed in the absorbing state s_j if starts in transient state s_i. Then B = NR, where N is the fundamental matrix and R is the canonical form.

IV IMAGE RECOMMENDATION FRAMEWORK AND ALGORITHM

A Image Recommendation Framework

The proposed framework presents online image retrieval similar to Google image search engine. In the retrieval phase, users submit queries which consist of keywords, to search relevant images of their interest. The search engine returns list of images. The framework includes two phases (1) Pre-processing phase and (2) Online Phase. Pre-processing phase includes step 1 and step 2. Online phase includes step 3 and step 4.

Step 1: Keyword Relevance Probability Construction

User submits a query to search engine and clicks on relevant images of his/her interest. Therefore, these query keywords give brief but comprehensive meaning of users need. To find logical connection between keywords, one step transition probability of Markov chain is calculated [25]. The user clicks image IMGi for given input query q, where keyword w_1 followed by keyword w_2. The current probability $p(w_1,w_2)$ is updated by using the Equation 2, where each keyword represents the state of the Markov chain.

$$p(w_1, w_2) = \frac{K * p(w_1, w_2) + k}{K + k} \qquad (2)$$

Where K is the number of unique keywords and k is the number of occurrence of keyword w_1 followed by w_2. Sometimes, images are annotated with single keyword. In such case, keyword relevance probability is calculated by considering keyword followed by itself. Therefore, relevance probability related to that image is considered as well as improved.

Whenever, a new keyword appears in the query, its initial state counter is set to 0, otherwise it is incremented and occurrence of keyword is measured. Similarly, if that keyword is followed by another keyword, its interstate link counter is also incremented and sequence of its occurrence is measured.

Step 2: Aggregate Markov Chain Construction

As users do not have enough knowledge about the information they are looking for, even in closely related images, the common keywords are very few. Hence state space of keywords is clustered to avoid this zero-frequency problem by constructing Aggregate Markov Chain (AMC) [25]. The AMC is constructed for all the queries of all images in log by using Equation 2 to model keyword relevance.

The steady state probability of AMC is calculated as follows:

1. In order to make AMC stochastic, add small value μ to all super-diagonal elements of AMC and subtract from any non-zero elements in the same diagonal.
2. Calculate $(AMC)^N$ by calculating its eigenvalues and eigenvectors as discussed in section III-A.

Step 3: Aggregate Absorbing Markov Chain Construction

To find relevant link between keywords of input query with annotated keywords, Aggregate Absorbing Markov Chain (AAbMC) is incorporated. AAbMC is constructed by using AMC obtained in step 2 and user input query. Keywords of input query are considered as absorbing states and other keywords in AMC represent the transient states. It is mainly focused on calculating probability by the transient states to reach the absorbing states. Therefore, relevant link between the keywords are efficiently calculated.

Let t be the keywords in transient states and r be the keywords in absorbing states (keywords of input query). The canonical form of the transition matrix of AAMC can be given as

$$P = \begin{array}{c c} & \begin{array}{cc} T & A \end{array} \\ \begin{array}{c} T \\ A \end{array} & \begin{pmatrix} Q & R \\ 0 & I \end{pmatrix} \end{array}$$

Where, Q is the t×t matrix, representing transition probabilities from keywords to keywords of transient states. R is the t × r matrix, representing transition probabilities from keywords of transient states to keywords of absorbing states. I is the r × r identity matrix. 0 is the r × t zero matrix.

The fundamental matrix for AAbMC is given by the matrix $F = (I - Q)^{-1}$. The entry f_{IJ} in F represents probability of number of occurrences of keywords in transient states. The AAbMC kernel MC is the t × r matrix obtained by multiplying matrix F with R, i.e., MC = F R. The entry mc_{IJ} in MC represents probability of transient keywords to reach absorbing keywords. It gives the required relevance between keywords of input query and other keywords of AMC.

Step 4: Markov Distance Calculation to Rank Images

In this step, the images are ranked by calculating Markov distance [25] between user input query and annotation related to images. Images are filtered based on their annotation similar to input query keywords. The AAbMC is calculated for each filtered image and the equilibrium state vector (steady state row vector) is obtained as discussed in section III-A.

For user input query q, the row vector i_Q represents the keywords of q, and r_i represents the row vector of each image. The Markov distance dm is calculated as given in Equation 3.

$$dm = (i_q - r_i)MC^T(i_q - r_i)^T \quad (3)$$

The images are ranked based on the sorted distance values.

B Algorithm

In this section, Image Recommendation with Absorbing Markov Chain (IRAbMC) algorithm as shown in Algorithm 1 is presented. It has two phase : Offline and Online. In Offline phase, keyword relevance probability for each image is calculated from annotated log-file. In online phase, for given user input query, keyword relevance is calculated from offline data and keywords of input query. Finally, images are retrieved and ranked.

Algorithm 1: IRAbMC : Image Recommendation with Absorbing Markov Chain

Input : Input Query q, Annotated log l
Output: Ranked Image List I = < 1..k >

begin
- Offline :
- Calculate keyword relevance probability for each image keywords in the annotated log l by using Equation 2.
- Calculate equilibrium state vector R = $\{r_1,r_2,...\}$ for each image as discussed in section III-A
- Calculate Aggregate Markov Chain AMC as discussed in step 2 of section IV-C.
- Online :
- **for** *input query* q **do**
  - Let query keywords A = $\{w_1,w_2,...\}$ be the absorbing states and remaining keywords of AMC be the transition states T = $\{w_I$, where $w_I \notin A\}$
  - Generate Aggregate Absorbing Markov chain AAbMC by using step 3 of section IV-C.
  - Let i_Q be the row vector of A.
  - Calculate Markov distance using i_Q , R and AAbMC using Equation 3.
  - Rank the images based on sorted distance values in ascending order.

V. EXPERIMENTS

A. Data Collection

In this experiment, publicly available ground-truth database [26], in which images are already annotated is used to evaluate the proposed method. This database has total 1109 images in 20 different clusters. Each cluster has about 55 images.

B. Experiment Setup

The setup of Image recommendation with absorbing Markov chain (IRAbMC) framework is as follows. Aggregate Markov Chain (AMC) is constructed to calculate keywords relevance probabilities between the annotated keywords. A small value μ which is close to zero is added to super-diagonal elements of AMC and subtracted from any random non-zero elements within the same line [25]. In this experiment, μ=0.02 is used in order to make the Markov chain as monodesmic chain and retain the stochastic property of the chain. Steady state probability of AMC, $(AMC)^N$ is calculated by using eigenvalues and eigenvectors of AMC. The results are obtained by considering *n=1*, *n=3*, *n=5*, *n=7* and *n=10*. For user input query, Aggregate Absorbing Markov Chain (AAbMC) is constructed by considering input query keywords as absorbing states of the $(AMC)^N$ and remaining states as transition states. Images are filtered such that their annotations are similar to the input query keywords and equilibrium state vector (row vector) is calculated for those images. Markov distance is calculated between user query and row vector of filtered images. Images are sorted and ranked based on the distance values.

The setup of Markov Semantic Indexing(MSI) [25] is as follows. Aggregate Markov Chain (AMC) is constructed to calculate keywords relevance probabilities between the annotated keywords. A small value μ = 0.02, which is close to zero is added to super-diagonal elements of AMC and subtracted from any random non-zero elements within the same line. Steady state probability of AMC, $(AMC)^N$ is calculated by using eigenvalues and eigenvectors of AMC. The results are obtained by considering *n=1*, *n=3*, *n=5*, *n=7* and *n=10*. Zero mean of $(AMC)^T$ is calculated by subtracting mean row from each row of it. Covariance matrix(CM) of resulting $(AMC)^T$ is calculated. Images are filtered such that their annotations are similar to the input query keywords and equilibrium state vector (row vector) is calculated for those images. Markov distance is calculated between user query q and row vector r_I of filtered images by Equation 4. Images are sorted and ranked based on the distance values.

$$dm = (q - r_I)CM(q - r_I)^T \quad (4)$$

C. Performance Evaluation

In this section, experiment results are presented and discussed. Image recommendation with absorbing Markov chain (IRAbMC) framework and Markov Semantic Indexing(MSI) are studied and compared. Experiments have been conducted on 4GB memory and Intel(R) Core(TM) i3-3217U CPU @ 1.80GHz processor. Dataset used in the experiments for IRAbMC and MSI are same as discussed in data collection. Top-5 image recommendations results are obtained for all 20 clusters for both the methods. A total of 100 queries, 5 from each cluster are considered for evaluation.

User evaluation is performed to evaluate ranking of image recommendations for both the methods. Ten graduate students are invited to grade the ranking results. Each student is assigned two clusters for evaluation. We have asked them to evaluate relevance between testing queries and recommended images ranking in the range of 0 to 1, in which 0 means totally irrelevant and 1 means totally relevant. Average values are calculated for top-1 to top-5 images. It is observed from the relevance score of ranking results that when $n=5$, images are ranked efficiently, hence for comparing results we have set $n=5$ to calculate steady state probability of AMC.

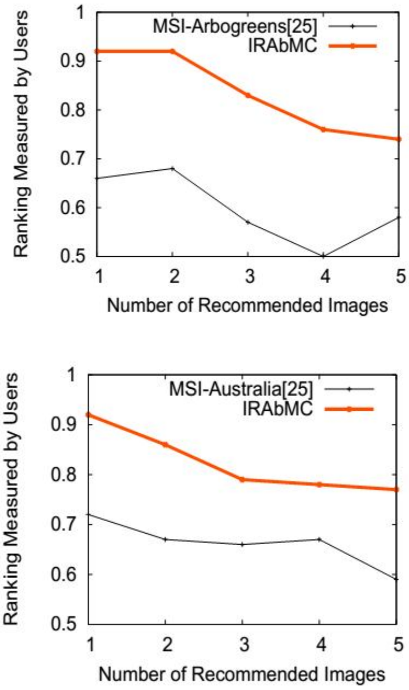

Fig 1. User Evaluation for Image Recommendations Ranking for *Arbogreens* and *Australia* clusters

Fig. 1-2 shows user evaluation ranking relevance score of image recommendations results with MSI and IRAbMC methods for four clusters. It is observed from all the graphs that for IRAbMC method images are ranked in proper order, i.e., the image relevance score is in decreasing order in all graphs for that query. Top-1 ranked images has highest relevance score and top-5 has least score. In MSI method all retrieved images are relevant but are not ranked properly. The average of overall relevance score of ranked images of all the clusters with IRAbMC method is better by 26.30% in comparison with MSI method.

In Fig 3, top-5 ranked recommended images are displayed for both the methods. Images [a-e] represent ranked images for MSI method and [f-j] represents ranked images for IRAbMC. It is observed from Fig. 3, that images [f-j] represents all the leafless trees related to given user query, but images [a-e] represents trees without leaf and also with leaf.

The IRAbMC method differs from MSI method in following ways, hence IRAbMC is outperforms MSI by ranking images in proper order relevant to user input query. (i) In IRAbMC, Aggregate Absorbing Markov Chain (AAbMC) is constructed by considering input query as absorbing states. Hence, the size of the Aggregate Markov Chain(AMC) is reduced. Consider AMC matrix size of $n \times n$ and number of absorbing states as k, then the size of resulting AAbMC is $k \times (n - k)$. As the absorbing states are the keywords of input query, k can be less than 10 because user enters short queries. (ii) In MSI, Markov distance is calculated by covariance matrix. Hence, Images are retrieved with the same ranking even-though the occurrence of keywords of input query is changed. For example, for input query *trees bush grass*, *bush trees grass* and *grass trees bush*, the ranking of images retrieved in MSI are same, but the ranking of images differs in the IRAbMC method. (iii) In MSI, all the images are considered to calculate Markov distance, but in IRAbMC, images are filtered based on their annotation similar to input query keywords. (iv) Images annotated with single keyword is not recognized while calculating keyword relevance probability in MSI.

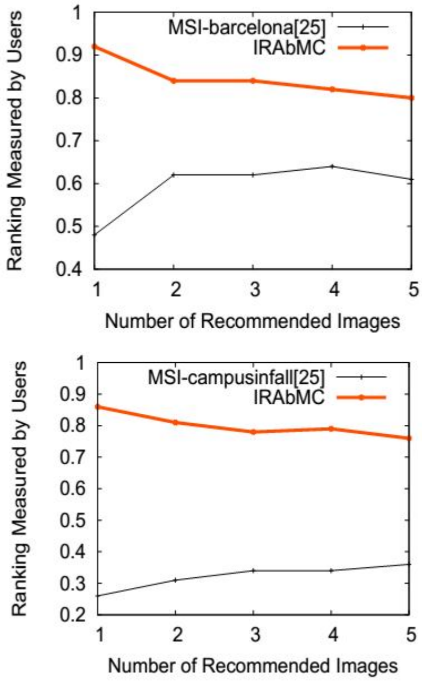

Fig 2. User Evaluation for Image Recommendations Ranking for *Barcelona* and *Campusinfall* clusters

VI. CONCLUSIONS

In this work, we have presented annotation based Image Recommendation with Absorbing Markov Chain (IRAbMC). Keyword relevance probability is calculated for annotated keywords for all the images. Absorbing Markov chain is incorporated to find relevant link between keywords of input query with annotated keywords. Images are filtered and ranke d by calculating Markov distance between user input query and annotation related to images. Experiments are performed on publicly available data provided by University of Washington and results are compared with Markovian

Semantic Indexing (MSI) method [25]. The proposed method outperforms MSI by providing more relevant images for given user query in proper order.

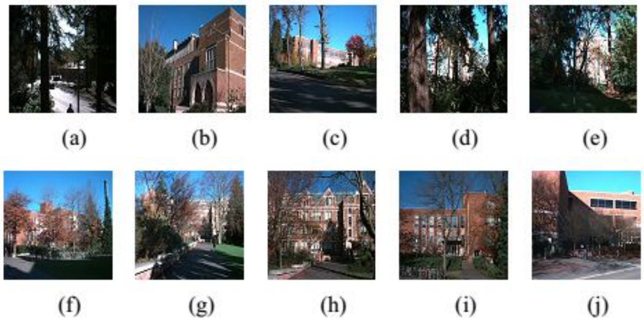

Fig. 3: Image Recommendations for query *leafless trees* for cluster *campusinfall*, images [a-e] and [f-j] shows results with MSI and IRAbMC method respectively

REFERENCES

[1] E. Akbas and F. T. Yarman Vural, "Automatic Image Annotat ion by Ensemble of Visual Descriptors," *CVPR '07: In the Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1– 8, 2007.

[2] I. Bartolini and P. Ciaccia, "Multi-dimensional Keywor d-based Image Annotation and Search," *In the Proceedings of the 2nd International Workshop on Keyword Search on Structured Data*, p. 5, 2010.

[3] C. Wang, F. Jing, L. Zhang, and H.-J. Zhang, "Content-bas ed Image Annotation Refinement," *CVPR'07 : In the Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1–8, 2007.

[4] J. Li and J. Z. Wang, "Real-time Computerized Annotation of Pictures," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30, no. 6, pp. 985–1002, 2008.

[5] K. Stevenson and C. Leung, "Comparative Evaluation of We b Image Search Engines for Multimedia Applications," *ICME 2005: In the Proceedings of IEEE International Conference on Multimedia and Expo*, pp. 4–14, 2005.

[6] B. Smyth, "A Community-based Approach to Personalizing Web Search," *IEEE Journal on Computer*, vol. 40, no. 8, pp. 42–50, 2007.

[7] J. Fan, Y. Gao, and H. Luo, "Integrating Concept Ontology and Multitask Learning to Achieve more Effective Classifier Tra ining for Multilevel Image Annotation," *IEEE Transactions on Image Processing*, vol. 17, no. 3, pp. 407–426, 2008.

[8] T.-T. Pham, N. E. Maillot, J.-H. Lim, and J.-P. Chevallet, "Latent Semantic Fusion Model for Image Retrieval and Annotation," *In the Proceedings of the Sixteenth ACM Conference on Information and Knowledge Management*, pp. 439–444, 2007.

[9] X.-J. Wang, L. Zhang, and W.-Y. Ma, "Duplicate Search Bas ed Image Annotation using Web Scale Data," *IEEE Journal of Electrical Engi-neering*, vol. 100, no. 9, pp. 2705–2721, September 2012.

[10] P. D. Shenoy, K. Srinivasa, K. Venugopal, and L. M. Patnaik, "Evolutionary Approach for Mining Association Rules on Dyn amic Databases," *Advances in Knowledge Discovery and Data Mining*, pp. 325–336, 2003.

[11] P. D. Shenoy, K. Srinivasa, K. Venugopal, and L. M. Patnaik, "Dynamic Association Rule Mining using Genetic Algorithms," *Intelligent Data Analysis*, vol. 9, no. 5, pp. 439–453, 2005.

[12] D. Sejal, C. Vinuth, M. Vijay, K. R. Venugopal, S. I. Sundaraja, and M. P. Lalit, "RSR : Related Search Recommendation with Us er Feedback Session," *In the Proceedings of the 9th European Conference on Data Mining 2015*, pp. 19–27, 2015.

[13] T. Hofmann, "Unsupervised Learning by Probabilistic L atent Semantic Analysis," *Journal on Machine Learning*, vol. 42, no. 2, pp. 177–196, 2001.

[14] D. Zhang, M. M. Islam, and G. Lu, "Structural Image Retri eval using Automatic Image Annotation and Region based Inverted File," *Journal of Visual Communication and Image Representation*, vol. 24, no. 7, pp. 1087–1098, 2013.

[15] D. Kılınc¸ and A. Alpkocak, "An Expansion and Reranking Approach for Annotation-based Image Retrieval from Web," *Journal of Expert Systems with Applications*, vol. 38, no. 10, pp. 13 121–13 127, 2011.

[16] M. M. Rahman, S. K. Antani, and G. R. Thoma, "A Learning-based Similarity Fusion and Filtering Approach for Biomedical Image Retrieval using SVM Classification and Relevance Feedback, " *IEEE Transactions on Information Technology in Biomedicine*, vol. 15, no. 4, pp. 640–646, 2011.

[17] E. Cheng, F. Jing, and L. Zhang, "A Unified Relevance Feed back Framework for Web Image Retrieval," *IEEE Transactions on Image Processing*, vol. 18, no. 6, pp. 1350–1357, 2009.

[18] A. Riad, H. Elminir, and S. Abd-Elghany, "Web Image Retr ieval Search Engine based on Semantically Shared Annotation," *International Journal of Computer Science Issues*, vol. 9, no. 3, pp. 223–228, March 2012.

[19] H. Kekre, S. D. Thepade, P. Mukherjee, S. Wadhwa, M. Kakaiya, and S. Singh, "Image Retrieval with Shape Features Extracted us ing Gradi-ent Operators and Slope Magnitude Technique with BTC," *International Journal of Computer Applications*, vol. 6, no. 8, 2010.

[20] X. He, D. Cai, and J. Han, "Learning a Maximum Margin Subs pace for Image Retrieval," *IEEE Transactions on Knowledge and Data Engineering*, vol. 20, no. 2, pp. 189–201, 2008.

[21] D. Liu, K. A. Hua, K. Vu, and N. Yu, "Fast Query Point Movem ent Techniques for Large CBIR Systems," *IEEE Transactions on Knowledge and Data Engineering*, vol. 21, no. 5, pp. 729–743, 2009.

[22] J.-M. Guo and H. Prasetyo, "Content Based Image Retriev al using Features Extracted from Halftoning-Based Block Truncation Coding,"*IEEE Transactions on Image Processing*, vol. 24, no. 3, pp. 1010–1024, 2015.

[23] Y. Gao, J. Peng, H. Luo, D. A. Keim, and J. Fan, "An Interac tive Approach for Filtering Out Junk Images from Keyword-based Google Search Results," *IEEE Transactions on Circuits and Systems for Video Technolog*, vol. 19, no. 12, pp. 1851–1865, 2009.

[24] *Absorbing Chains by Tim Carroll, Sheiva Sajadpour and Jesus Gonzalez [Online], http://www.docstoc.com/docs/160730932/Introduction-to-Absorbing-Chains.*

[25] K. A. Raftopoulos, K. S. Ntalianis, D. D. Sourlas, and S. D. Kollias, "Mining User Queries with Markov Chains: Application to Onl ine Image Retrieval," *IEEE Transactions on Knowledge and Data Engi-neering*, vol. 25, no. 2, pp. 433–447, 2013.

[26] L. G. Shapiro, "Ground Truth Database, Washington Univ ersity," *http://imagedatabase.cs.washington.edu/groundtruth/*, 2012.