IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume-3, Issue-9 E-ISSN: 2347-2693

User Review Based Content Image Retrieval Using Voronoi Algorithm

A.Kalaiyarasi[1*] and R.Mala[2]

[1*,2] *PG and Research Department of Computer Science, Maruthupandiyar College, Thanjavur.*

www.ijcseonline.org

Received: Aug/22/2015 Revised: Aug/30/2015 Accepted: Sep/24/2015 Published: Sep/30/2015

***Abstract*—** Relevance input is a fit inquiry change technique in the field of substance based picture retrieval. The key issue in relevance input is how to enough use the input information to improve the retrieval performance. This paper presents a relevance input scheme using Voronoi network model on the other hand input information adoption. Critical images during previous cycles are sensibly incorporated into the current cycle and the chosen critical images can better capture user's information need.

***Keywords*—** Relevance Feedback, Substance Based Picture Retrieval, Critical Picture Adoption, Voronoi Network.

I. Introduction

The rapid development of web and mixed media information has come about in the development of mixed media information retrieval techniques, especially the substance based picture retrieval (CBIR). CBIR framemeets expectations extract visual highlights from the images automatically. Similarities between two images are measured in terms of the contrasts between the relating features.

To take into account the subjectivity of human observation and bridge the gap between the high-level concepts and the low-level features, relevance input has been proposed to enhance the retrieval performance. During the process of picture retrieval, the client specifies the relevance of the retrieved objects, and the structure will then refine the inquiry results by learning from this information. A variety of relevance input techniques have been proposed. The main algorithms include highlight re-weighting and inquiry point movement (rui, huang, ortega and mehrotra 1998, ishikawa, subramanya and faloutsos 1998), Voronoi target search (cox, miller, minka, papathomas and yianilos 2000), support vecton the other hand machine active learning (hong, tian and huang 2000), and two class learning (macarthur, brodley and shyu 2000).

The key issue in relevance input is how to enough use the information provided from client input to increase the retrieval accuracy.

Most current CBIR framemeets expectations use the information given in one pass at each cycle and the refined inquiry is treated just like a starting query. Since the input information from the previous cycles and the next cycle does not straightforwardly connect, the majon the other hand problem of their approach is that when the next cycle of retrieval is started the information from previous cycles is practically lost. Alternatively we may continuously use all the critical images accumulated form the very beginning to fully use the information. However, it is still not an ideal resolution. With the progress of the retrieval process, there might exist diverse levels of relevance among all the objects that have been marked "relevant" before. Some of them are still highly critical while others might become neutral on the other hand indeed irrelevant. In another word, the client inconsistency might happen at each cycle of relevance judgments which will impair the retrieval results.

The commitment of this paper is to propose a scheme fon the other hand optimization in using the client input information. We investigate Voronoi network as a critical picture reception model to select a number of great points composing the positive input information. It is based on the assessment of the conviction values of the critical picture nodes in the network such that these conviction values can be used as probabilistic measure of usability of the critical images. By this approach, objects considered critical during previous cycles are sensibly incorporated and the chosen critical images can better capture user's information need than previous methods.

The remainder of this paper is sorted out as follows: section 2 presents and overview of Voronoi network and the proposed model fon the other hand critical picture adoption. Section 3 portrays the process of inference propagation and our main algorithm. Conclusions are given in section 4 with a discussion of future research works.

II. A Voronoi Structure on the other Hand Relevant Feddback

2.1 Voronoi Conviction Network

A Voronoi conviction network is a graphical representation of a set of discretionary variables and their dependencies. It provides an effective learning representation which imitates learning structures used by the human mind.

It has been widely used in textual information retrieval fon the other hand a long time (baeza-yates and ribeiro-neto 1999). In a Voronoi network, vertices in the chart represent the discretionary variables $X=\{x_1, x_2, K, x_n\}$ and direct arcs correspond to conditional conditions between variables. The folks of a hub xi can be meant by $pa(x_i)$. Each variable is independent of its i descendants given its prompt folks in the network. The interactions between nodes are represented by the conditional probability $p(x_i \mid pa(x_i))$. Other components that are contained in a Voronoi network include: (a) prion the other hand beliefs: the initial convictions of nodes in the network; (b) evidences: observations that are inputs to the network; (c) posterion the other hand probabilities: the last computed convictions after the confirmations have been propagated through the network (luo and savakis 2001). By applying the conditional probabilities between nodes and the indecencies between a hub and its non-descendants, the joint probability distribution over the complete set of variables can be expressed as:

$$P(X) = P(x_1, x2, K, x_n) = \prod_{i=1}^{n} P(xi \mid Pa(x_i)) \quad (1)$$

Therefore, a complicated joint probability distribution can be reduced to a set of conditional probability which are less demanding to characterize. More details of Voronoi network can be found in (pearl 1988, Heckerman 1995, Jensen 1998). We found that fon the other hand our critical picture reception problem, Voronoi network offers distinct advantages. Due to the subjectivity of human observation and the mechanism of relevance feedback, user's input judgment is not performed through exact match. User's preference is continuously reflected by the probabilities. Voronoi network models the probabilistic relationships among the objects, which make it suit fit to handles situation relating to probability disseminations over variables. Furthermore, the architecture representation of Voronoi network is highly adaptive and easy to build. Voronoi network provides a good framework for integrating the feature representations and it offers easy maintenance when adding new features. The flexibility of feature updating of conditional probabilities related with the direct links in the network fon the other hand our purpose. The diagram of the proposed Voronoi network generally, the network consists of layer, highlight index layer and critical picture layer. The root hub is the inquiry layer speaking to the query example picture given by the user. The middle of the road layer is highlight index layer which can be further isolated into two levels. The first level contains low-level feature representations, such as color, surface and shape. The second level is made by the components of the highlight vectors. The critical picture layer consists of the individual critical images determined by the user. The network is diverse with various inquiry examples and diverse critical images. New determined critical images get included to the critical picture layer as we move from one cycle of input to the next. All nodes in the network are related with a conviction value and all the direct associations between the nodes are related with a join weight, which is represented by a conditional probability.

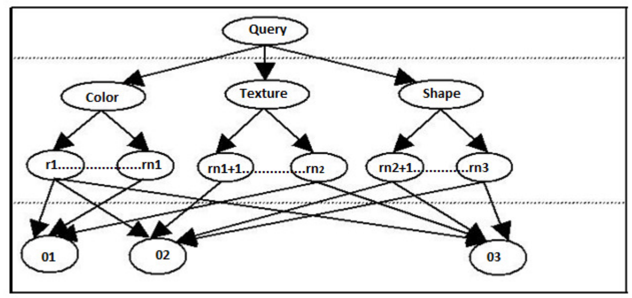

Figure 1: Voronoi network fon the other hand Critical Image Adoption

The join weight from the inquiry hub to the highlight index hub determined by $p(fi \mid q)$ reflects the emphasis of that feature representation in user's information need. The two levels of highlight index layer are joined by weighted incorporation is prefer fit in our application.

2.2 Voronoi Network Relevance Feedback Model

To apply Voronoi network to our application for critical picture adoption, we need to first formulate the problem in terms of creating a set of variables speaking to the distinct elements. Then settle the dependency relationships between the variables that is, creating the links from the parent nodes to tyke nodes. After that, the numeric probabilities fon the other hand each verify and join need to be assessed. In (Wilson, Srinivasan and indrawn 2000), they proposed a Voronoi network image retrieval engine searching the whole picture database to find the retrieval results. In our work, we develop a similar network, but only to process the critical images. Our network aggregates all the highlights compared with their separate net meets expectations for each highlight in the highlight set. Moreover, our Voronoi network model is a dynamic model which can be adjusted with diverse critical images determined by the user. We have also created a different mechanism on the other hand the links $p(rj|fi)$ speaking to the diverse contributions of the segment To that highlight vector. The join weights $p(fi|q)$ and $p(rj|fi)$ can be calculated By inter-weight updating and intra-weight updating algorithms proposed in (Rui, Huang, Ortega and Mehrotra 1998). The weight of A join from the highlight vector the other hand hub To the critical picture hub represented by $p(ok| rj)$ is hard to be gotten directly. However, it can be calculated using Bayes' rule:

$$p(o_k \mid r_j) = \frac{p(r_j \mid o_k)p(o_k)}{p(r_j)} \quad (2)$$

Here $p(rj)$ and $p(ok)$ are prior belief values of the segment rj and the critical picture ok. All components of highlight vectors and all critical images are assumed to have break indeed with prion the other hand beliefs. Therefore, $p(rj)$ is equivalent to 1 n_3 and $p(o)$ is equivalent to 1 m . The weight $p(r|o_k)$ represents the significance of segment rj in the critical image ok. We propose a distance-based approach to calculate this weight. Intuitively, if the distance between the component rj of the relevant image and that of the query image is small, it means that the component rj is important for the relevant image ok. On the other hand, if the distance is large, then rj is not an ideal component. Based on this analysis, the inverse of the distance can be a good estimation of weight $P(r_j|o_k)$. Thus $P(r_j|o_k)$ is calculated as follows:

$$p(r_j \mid o_k) = \frac{1}{d_{jk}} \quad (3)$$

Where d_{jk} is the distance of relevant image ok and the query example on component rj. These weights are then normalized to make the sum of the weights equal to 1:

$$p(r_j \mid o_k) = \frac{p(r_j \mid o_k)}{\sum_j p(r_j \mid o_k)} \quad (4)$$

After the weights of links and the prior beliefs of all the nodes in the network have been assigned, we can initialize the query node and perform the inference propagation throughout the network to update the belief values of all the relevant image nodes. Then theses belief values can be used as the probabilistic ranking of the relevant images. The details of the inference process and how to select relevant images will be discussed in the next section.

III. Network Evaluation for Relevant for Image Adoption

The approach for relevant image adoption in the Bayesian network model is based on the idea that, by learning user's feedback information, the system obtains new evidence about the current relevance level for all the relevant images to the query. At each stage of iteration, the belief values of all the relevant image nodes in the network are re-evaluated according to the result of query and user's relevance feedback.

The query example image can be treated as evidence, which will be instantiated with $P(q)=1$ when the network is evaluated. The belief values across the network are updated given the initial evidence. According to the topology of our Bayesian network, the inference process propagates from the query layer through the feature index layer to relevant image layer. Currently, there are many efficient methods for exact inference and approximate inference in Bayesian network. Although exact inference in general for an arbitrary Bayesian network is NP-hard (Cooper 1990), it is still efficient for some classes of Bayesian networks. Considering that the size of our network is not large, we employ exact inference method. One of the most influential methods for exact inference is tree-clustering that transforms the network into a so-called junction tree (Jensen, Lauritzen & Olesen, 1990). The junction tree basically clusters the variables in such a way that all loops in the network are removed and the clusters are as small as possible. After converting the network to a tree, the message passing scheme (Pearl 1988) can be run on this tree to update the beliefs of each node in the network given the observation of evidence.

After the inference propagation, the belief values of all the relevant image nodes represented by $\{b(o_k) = P(o_k \mid q), k = 1,2,\ldots.m\}$ are assessed and used as the probabilistic ranking of the relevant images. The candidate relevant image set then can be obtained as follows:

$$S = \{o_1, o_2, \ldots, o_l\}, \quad b(o_k) > \tau \quad (5)$$

Where τ is a constant limit which can be estimated by the training process. Using these critical images as our positive input information, we can employ a discretionary relevance input calculation to obtain the next cycle of retrieval objects.

After the inference process is performed, all the weights of links are overhauled fon the other hand the next cycle of feedback. Too the network beliefs at time t simply become the prion the other hand convictions fon the other hand the cycle t+1. This process repeats at each stage of input until the retrieval process is over and the client is satisfied with the retrieval results. The calculation fon the other hand our critical picture reception is described as follows:

1. After the initial feedback, all the critical images are used to develop the Bayesian network and the join weights are calculated.
2. Perform the inference propagation to update the conviction values of all the nodes in the network.
3. Select the critical images whose conviction is above the limit as the positive input information.
4. Update the join weights using the chosen critical images.

5. The overhauled conviction values are set as new prion the other hand convictions fon the other hand the next iteration.
6. Start a new cycle of retrieval using the overhauled positive input information.
7. On the off chance that the client proceeds to give input judgment
8. New critical objects get included to the network.
9. Go back to step 2 with the overhauled weights and prion the other hand beliefs.
10. Else stop the retrieval process and wait fon the other hand the new query.

III. Conclusion and Future Work

In this paper, we have focused on the problem of improving the effectiveness in using the critical images given by user's feedback. We propose an approach using Bayesian network as the critical picture reception model to find the ideal objects. We accept that Bayesian network is a fit tool that is application in the point of view of relevance input in picture retrieval. As of now the execution of the structure is under test and the effectiveness of our approach is being evaluated. The precision rate as a function of the number of input cycles will be used as the execution measure. The ongoing expansions to the work involve the partition of the critical images. Other than the critical picture adoption, the clustering of the chosen critical images can be done to further illuminate the user's information need. One on the other hand more clusters which the chosen critical images belong to will be set as positive input information.

In addition, the possible change of the network structure includes the semantic level highlight index being incorporated into the network and mapped to the low-level features. The utilization of negative input will too be investigated.

References

[1] Jun-yi Wang ; Coll. of Comput. Sci., Inner Mongolia Univ., Huhhot, China ; Xin-ming Ye, "The study of methods for language model based positive and negative relevance feedback in information retrieval", Published in: Intelligent Computing and Intelligent Systems (ICIS), 2010 IEEE International Conference on (Volume:3) Date of Conference: 29-31 Oct. 2010 Page(s):870 – 873.

[2] Chen Chen ; Coll. of Inf. Tech., Sci. Nankai Univ., Tianjin, China ; Hou Chunyan ; Yuan Xiaojie, "Relevance Feedback Fusion via Query Expansion", Published in: Web Intelligence and Intelligent Agent Technology (WI-IAT), 2012 IEEE/WIC/ACM International Conferences on (Volume:3) Date of Conference: 4-7 Dec. 2012 Page(s): 122 – 126.

[3] Zhang, Wen-jing ; Wang, Jun-yi, "The Study of Methods for Language Model Based Positive and Negative Relevance Feedback in Information Retrieval", Published in: Information Science and Engineering (ISISE), 2012 International Symposium on Date of Conference: 14-16 Dec. 2012 Page(s): 39 – 43.

[4] Hoi, S.C.H. ; Dept. of Comput. Sci. & Eng., Chinese Univ. of Hong Kong, China ; Lyu, M.R. ; Rong Jin, "A unified log-based relevance feedback scheme for image retrieval", Published in: Knowledge and Data Engineering, IEEE Transactions on (Volume:18 , Issue: 4) Page(s): 509 – 524 ISSN : 1041-4347.

[5] Araujo, M.R.B. ; Comput. Sci. Dept., Univ. of Sao Paulo, Sao Carlos, Brazil ; Traina, A.J.M. ; Traina, A. ; Bueno, J.M., "Extending relational databases to support content-based retrieval of medical images", Published in: Computer-Based Medical Systems, 2002. (CBMS 2002). Proceedings of the 15th IEEE Symposium on Date of Conference: 2002 Page(s): 303 – 308.

[6] Chhasatia, N.J. ; Dept. of EC, G.H. Patel Coll. of Eng. & Technol., Anand, India ; Trivedi, C.U. ; Shah, K.A., "Performance evaluation of localized person based scene detection and retrieval in video", Published in: Image Information Processing (ICIIP), 2013 IEEE Second International Conference on Date of Conference: 9-11 Dec. 2013 Page(s): 78 – 83.

[7] Juan Cheng ; Univ. of Inf. Eng., Henan, China ; Xijian Ping, "Text image retrieval based on generalized normalized picture information measure", Published in: Natural Language Processing and Knowledge Engineering, 2005. IEEE NLP-KE '05. Proceedings of 2005 IEEE International Conference on Date of Conference: 30 Oct.-1 Nov. 2005 Page(s): 503 – 505.

[8] Chhasatia, N.J. ; G.H. Patel Coll. of Eng. & Technol., Anand, India ; Trivedi, C.U. ; Shah, K.A. ; Mankodi, P.R., "Genre based video retrieval using similarity function between feature vectors", Published in: Computational Intelligence and Computing Research (ICCIC), 2013 IEEE International Conference on Date of Conference: 26-28 Dec. 2013 Page(s): 1 – 7.

[9] Bueno, J.M. ; Comput. Sci. Dept., Sao Paulo Univ., Brazil ; Chino, F. ; Traina, A.J.M. ; Traina, A.J.M., "How to add content-based image retrieval capability in a PACS", Published in: Computer-Based Medical Systems, 2002. (CBMS 2002). Proceedings of the 15th IEEE Symposium on Date of Conference: 2002 Page(s): 321 – 326.

[10] Doyle, R. ; NMRC, Cork, Ireland ; Hentzell, H., "EUROPRACTICE-MCM: a European initiative to create an MCM infrastructure and to stimulate commercial MCM take-up", Published in: Multichip Modules, 1997., International Conference on Date of Conference: 2-4 Apr 1997 Page(s): 14 – 18.

[12] Rondovic, B. ; Fac. of Econ., Univ. of Montenegro, Podgorica, Montenegro ; Lazovic, V. ; Popovic, Z. ;

Durickovic, T., “Determinants of electronic commerce - the factors of acceptance in Montenegro”, Published in: Information and Communication Technology, Electronics and Microelectronics (MIPRO), 2015 38th International Convention on Date of Conference: 25-29 May 2015 Page(s): 1475 – 1480.

[14] Rey, J.C. ; Mentor Graphics Corp., San Jose, CA ; Nagaraj, N.S. ; Kahng, A. ; Aitken, R., “DFM in practice: Hit or hype?”, Published in: Design Automation Conference, 2008. DAC 2008. 45th ACM/IEEE Date of Conference: 8-13 June 2008 Page(s): 898 – 899.

[15] Di Giacomo, T. ; MIRALab, Univ. of Geneva, Switzerland ; Joslin, C. ; Garchery, S. ; Magnenat-Thalmann, N., “Adaptation of facial and body animation for MPEG-based architectures”, Published in: Cyberworlds, 2003. Proceedings. 2003 International Conference on Date of Conference: 3-5 Dec. 2003 Page(s): 221 – 228.