Neurocomputing 72 (2009) 2046–2051

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

Letters

A biased minimax probability machine-based scheme for relevance feedback in image retrieval

Xiang Peng *, Irwin King

Department of Computer Science and Engineering, The Chinese University of Hong Kong, Shatin, N.T., Hong Kong

ARTICLE INFO

Article history:
Received 30 April 2007
Received in revised form
3 November 2008
Accepted 7 November 2008
Communicated by T. Heskes
Available online 9 December 2008

Keywords:
Biased minimax probability machine
Relevance feedback
Content-based image retrieval

ABSTRACT

In recent years, minimax probability machines (MPMs) have demonstrated excellent performance in a variety of pattern recognition problems. At the same time various machine learning methods have been applied on relevance feedback tasks in content-based image retrieval (CBIR). One of the problems in typical techniques for relevance feedback is that they treat the relevant feedback and irrelevant feedback equally. Since the negative instances largely outnumber the positive instances, the assumption that they are balanced is incorrect as the data are biased. In this paper we study how biased minimax probability machine (BMPM), a variation of MPM, can be applied for relevance feedback in image retrieval tasks. Different from previous methods, this model directly controls the accuracy of classification of the future data to construct biased classifiers. Hence, it provides a rigorous treatment on imbalanced dataset. Mathematical formulation and explanations are provided to demonstrate the advantages. Experiments are conducted to evaluate the performance of our proposed framework, in which encouraging and promising experimental results are obtained.

1. Introduction

With the recent progress of hardware for capturing and storing image data, content-based image retrieval (CBIR) has attracted a lot of research interests in the past decades [1,10,11,16]. However, two semantically similar images may be located far from each other in the feature space, while two absolutely different images may lie close to each other. This is known as the problem of *semantic gap* between low-level features and high-level concepts [14]. Relevance feedback has been shown to be a powerful tool to address this problem and improves retrieval performance in CBIR [15,17].

Recently, researchers have proposed a number of classification techniques to tackle relevance feedback tasks including some state-of-the-art models such as support vector machine (SVM) [5–7]. However, most of the classification techniques treat the relevance feedback problem as a strict binary classification problem and often they do not consider the imbalanced dataset problem, which means the number 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). An illustration is shown in Fig. 1.

Minimax probability machine (MPM) has been used as a novel and important tool to perform classification tasks [12]. Compared with traditional classification models, it has a promising accuracy performance on pattern recognition tasks. In order to tackle the problem of imbalanced dataset in CBIR, we propose to use a modified MPM, called biased minimax probability machine (BMPM) which can better model the relevance feedback problem and reduce the accuracy degradation caused by the imbalanced dataset problem. Although BMPM has been applied to some areas and problems earlier, such as text classification and medical diagnosis, it is the first time to employ this model to handle the relevant feedback problem in CBIR. We show in this work that the BMPM model has better performance compared to previous methods.

The rest of this paper is organized as follows. Section 2 reviews some related work on relevance feedback and MPM. Section 3 formulates the relevance feedback technique employing BMPM and shows the benefits when compared with conventional techniques. Performance evaluations are reported in Section 4. Finally, we conclude our work and describe some potential research directions in Section 5.

2. Related work

Relevance feedback takes advantage of human–machine interaction to refine high-level queries represented by low-level features [2,6]. It is employed in conventional document retrieval

* Corresponding author. Tel.: +852 26098431; fax: +852 26035024.
E-mail addresses: xpeng@cse.cuhk.edu.hk, csxpeng@gmail.com (X. Peng).

0925-2312/$ - see front matter Crown Copyright © 2008 Published by Elsevier B.V. All rights reserved.
doi:10.1016/j.neucom.2008.11.020

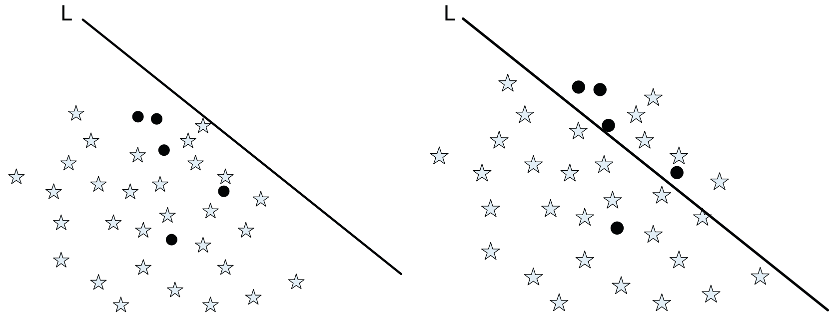

Fig. 1. Imbalanced classification illustration. The overall classification accuracy is 86%, while the accuracy for the more important class is 0% (labelled as '●') (left). The overall classification accuracy is 83%, while the accuracy for the more important class is 80% (labelled as '●') (right).

for automatically adjusting an existing query using information fed back from the user. In image retrieval applications, the user selects relevant images from previous retrieved results and provides a preference weight for each relevant image. The weights for the low-level feature, i.e., color and texture, etc., are dynamically updated based on the user's feedback. The user is no longer required to specify a precise weight for each low-level feature to formulate the query model. Based on the feedback, the high-level concepts implied by the feature weights and relevant feedbacks are automatically refined.

Meanwhile, classification models are widely employed to handle relevance feedback problem in current literature. We here introduce the basic concept of MPM [12]. In pattern classification problems, MPM provides very good empirical generalization performance.

Let us illustrate MPM in a binary classification case. Suppose two random n-dimensional vectors, $\mathbf{x}$ and $\mathbf{y}$, represent two classes of data, where $\mathbf{x}$ belongs to the family of distributions with a given mean $\bar{\mathbf{x}}$ and a covariance matrix $\Sigma_{\mathbf{x}}$, denoted as $\mathbf{x}\sim(\bar{\mathbf{x}},\Sigma_{\mathbf{x}})$; similarly, $\mathbf{y}$ belongs to the family of distributions with a given mean $\bar{\mathbf{y}}$ and a covariance matrix $\Sigma_{\mathbf{y}}$, denoted as $\mathbf{y}\sim(\bar{\mathbf{y}},\Sigma_{\mathbf{y}})$. Here $\mathbf{x},\mathbf{y},\bar{\mathbf{x}},\bar{\mathbf{y}}\in\mathbb{R}^n$ and $\Sigma_{\mathbf{x}},\Sigma_{\mathbf{y}}\in\mathbb{R}^{n\times n}$. In the following discussion of this work, $\mathbf{x}$ represents the relevance image class and $\mathbf{y}$ represents the irrelevance image class.

The MPM attempts to determine the hyperplane $\mathbf{a}^{\mathrm{T}}\mathbf{z}=b$ ($\mathbf{a}\in\mathbb{R}^n,\mathbf{z}\in\mathbb{R}^n,b\in\mathbb{R}$) which can separate two classes of data with maximal probability. The formulation for the MPM model [13] is written as follows:

$$\begin{aligned}\max_{\alpha,\mathbf{a}\neq\mathbf{0},b}\quad & \alpha\\ \text{s.t.}\quad & \inf_{\mathbf{x}\sim(\bar{\mathbf{x}},\Sigma_{\mathbf{x}})}\mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{x}\geqslant a\}\geqslant\alpha,\\ & \inf_{\mathbf{y}\sim(\bar{\mathbf{y}},\Sigma_{\mathbf{y}})}\mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{y}\leqslant b\}\geqslant\alpha,\end{aligned}\tag{1}$$

where α represents the lower bound of the accuracy for future data. Future points $\mathbf{z}$ for which $\mathbf{a}^{\mathrm{T}}\mathbf{z}\geqslant\alpha$ are then classified as the class $\mathbf{x}$; otherwise, they are judged as class $\mathbf{y}$.

Later, Huang et al. [8] improved the model by removing the assumption that these two classes have the same importance, and furthermore adding a bias to the more important class. As we could observe from the above formulation, this model actually assumes that two classes have the same importance. Hence it makes the worst-case accuracies for two classes the same. However, in real applications, especially in relevance feedback of CBIR, two classes of data are usually biased, i.e., the relevant class is often more important than the irrelevance class and the quantities of both datasets are imbalanced. Therefore it is more appropriate to take the inherited bias into account in this context.

3. Relevance feedback using BMPM

In this section, we will first give a more detailed introduction on BMPM. Next, we show the benefits of applying BMPM in relevance feedback in CBIR. We then present how the BMPM-based approach can be employed for relevance feedback tasks in Section 3.3.

3.1. Model definition

Given reliable $\{\bar{\mathbf{x}},\Sigma_{\mathbf{x}}\}$, $\{\bar{\mathbf{y}},\Sigma_{\mathbf{y}}\}$ for two classes of data, we try to find a hyperplane $\mathbf{a}^{\mathrm{T}}\mathbf{z}=b$ ($\mathbf{a}\neq 0,\mathbf{z}\in\mathbb{R}^n,b\in\mathbb{R}$) with $\mathbf{a}^{\mathrm{T}}\mathbf{z}>b$ being considered as class $\mathbf{x}$ and $\mathbf{a}^{\mathrm{T}}\mathbf{z}<b$ being judged as class $\mathbf{y}$ to separate the important class of data $\mathbf{x}$ with a maximal probability while keeping the accuracy of less important class of data $\mathbf{y}$ acceptable.[1] We formulate this objective as follows:

$$\begin{aligned}\max_{\alpha,\beta,b,\mathbf{a}\neq\mathbf{0}}\quad & \alpha\\ \text{s.t.}\quad & \inf_{\mathbf{x}\sim(\bar{\mathbf{x}},\Sigma_{\mathbf{x}})}\mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{x}\geqslant b\}\geqslant\alpha,\\ & \inf_{\mathbf{y}\sim(\bar{\mathbf{y}},\Sigma_{\mathbf{y}})}\mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{y}\leqslant b\}\geqslant\beta,\\ & \beta\geqslant\beta_0,\end{aligned}\tag{2}$$

where α represents the lower bound of the accuracy for the classification, or the worst-case accuracy of future data points $\mathbf{x}$, similar to $\boldsymbol{\beta}$. The parameter β_0 is a pre-specified positive constant, which represents the acceptable accuracy level for the less important class $\mathbf{y}$.

The above formulation is derived from MPM, which requires the probabilities of correct classification for both classes to be an equal value α. Through this formulation, the BMPM model can handle the imbalanced classification by changing the value of α and $\boldsymbol{\beta}_0$. This model provides a different treatment on different classes, i.e., the hyperplane $\mathbf{a}^{*\mathrm{T}}\mathbf{z}=b^*$ given by the solution of this optimization will favor the classification of the important class $\mathbf{x}$ over the less important class $\mathbf{y}$. Furthermore, the derived decision hyperplane is directly associated with two real accuracy indicators of classification of the future data, i.e., α and β_0, for each class.

3.2. Advantages of BMPM in relevance feedback

From the above formulations, one could see that the optimization in BMPM is similar to the one in the MPM, which is in SOCP format and could be efficiently solved by SeduMi or Mosek. Now, we show the mathematical differences and the advantages of our proposed BMPM framework from an analytical perspective for

[1] The readers may refer to [8] for a more detailed and complete description.

solving the relevance feedback problems compared with SVMs and other conventional learning methods (Fig. 2).

Obviously we see that BMPM is with the following constraints, in contrast to the one of MPM in Eq. (1),

$$\inf_{\mathbf{x}\sim(\bar{\mathbf{x}},\Sigma_{\mathbf{x}})} \mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{x} \geqslant b\} \geqslant \alpha,$$
$$\inf_{\mathbf{y}\sim(\bar{\mathbf{y}},\Sigma_{\mathbf{y}})} \mathbf{Pr}\{\mathbf{a}^{\mathrm{T}}\mathbf{y} \leqslant b\} \geqslant \beta,$$
$$\beta \geqslant \beta_0. \tag{3}$$

The difference indicates that the proposed BMPM framework tries to improve the accuracy of relevant images while maintaining an acceptable specificity of irrelevant ones. This methodology provides a rigorous way to handle the relevance feedback problem by directly controlling the classification accuracy and this is powerful for solving the imbalanced dataset problem in CBIR. However, SVMs and other traditional learning models treat the two classes without any bias or direct control, which is not effective to model and solve the relevance feedback problem.

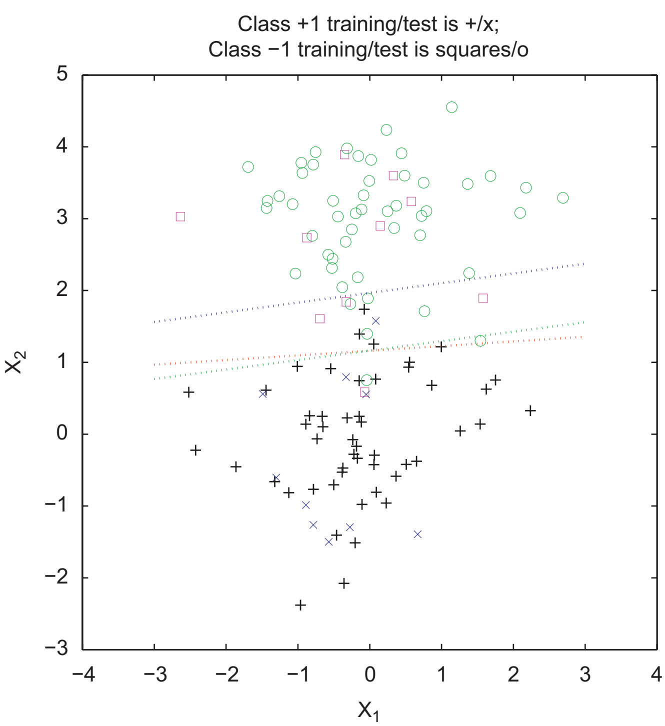

Fig. 2. Decision lines comparison: MPM decision line (dotted red line), BMPM decision line (dotted green line), SVM decision line (dotted blue line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3. *Relevance feedback framework by BMPM*

In this section we describe how to formulate the relevance feedback algorithm by employing the BMPM technique. Applying the BMPM-based technique in relevance feedback is similar to conventional classification tasks. However, the relevance feedback needs to construct an iterative function to produce the retrieval results. Fig. 3 is our proposed approach for retrieval task in CBIR.

After a certain number of iterations of relevance feedback finished, our proposed strategy returns the *Top-n* most relevant images and also learn a reasonable classifier to classify the imbalanced image dataset.

4. Experiments

We implement BMPM-based learning scheme and apply to relevance feedback in CBIR. In this section, we describe the iterative framework and show the experimental results. We compare the performance of our proposed approach with two classification models for relevance feedback: MPM and SVM. The SVM algorithm deployed in our experiments is based on modifying the codes in the *libsvm* library, and MPM and BMPM schemes are adopted from the MPM and BMPM packages, respectively. Furthermore we choose the same kernel and parameters (such as α, β_0, etc.) for all the settings. The experiments are evaluated on both a synthetic dataset and a real-world image dataset. All our works are done on a 3.2 GHz machine with Intel Pentium 4 processor and 1 Gb RAM, and the OS is Windows XP Version 2002 (Table 1).

Table 1
List of synthetic dataset.

Dataset	# Instances	# Features	# Classes
Synthetic dataset	1000	2	10

Algorithm *BMPM-based Relevance Feedback*
Input: $\mathbf{Q}_{im}$ (query image)
Output: $\mathbf{R}_{im}$ (images belong to the relevant class with similar semantic content)
1. $\mathbf{F}_q \Leftarrow \mathbf{Q}_{im}$ /* Feature extraction for query image */
2. $\mathbf{F}_q \Leftarrow \mathbf{x}/\mathbf{y}$ /* Assign label to query image */
3. **For** i = 1: MaxIt
4. $\quad\mathbf{R}_{im} \Leftarrow \mathbf{R}^i_{im}$ /* Update based on similarity measurement */
5. $\quad$Involve feedback information using BMPM
6. $\quad\quad\mathbf{R}^1_{im}, \mathbf{R}^2_{im} \Leftarrow \mathbf{R}_{im}$ /* Separate returned images into two sets */
7. $\quad\quad\mathbf{R}^1_{im}, \mathbf{R}^2_{im} \Leftarrow \{\mathbf{x}, \mathbf{y}\}$ /* Assign labels to classes by experts */
8. $\quad\quad$Classification task by BMPM
9. $\quad i \Leftarrow i + 1$
10. **End For**
11. **Return** $\mathbf{R}_{im}$

Fig. 3. BMPM-based relevance feedback.

4.1. Experiment datasets

4.1.1. Synthetic dataset

We generate a synthetic dataset to simulate the real-world images. The dataset consists 10 categories, nine of which contains 100 data points randomly generated by Gaussian distribution with different means and covariance matrices in a two-dimensional space. The remaining class contains 100 instances generated by a different mean and covariance matrix, representing the relevant samples (Table 2).

4.1.2. Real-world dataset

The real-world dataset is chosen from the COREL image CDs. We organize one dataset which contains various images with different semantic meanings, such as *bird*, *pyramid*, *model*, *autumn*, *dog*, and *glacier*, etc. It is with six categories (we name it 6-Bird). The class of *bird* which we recognize as the positive class contains 50 images. The other five categories with each including 100 instances are regarded as the negative class (Fig. 4).

Here we extract three different features to represent the images: *color*, *shape*, and *texture*. The color feature employed is the color histograms. We quantize the number of pixels into 10 bins for each color channel (Hue, Saturation, and Value), respectively. Then we obtain a 30-dimensional color histogram. We use edge direction histogram as shape feature to represent the images [9]. First we compute the edge images by the Canny edge detector and obtain the edge direction histogram by quantizing the results into 15 bins of 24°. Therefore a 15-dimensional edge direction histogram is used as the edge feature. We apply the wavelet-based texture in our experiments [18]. Gabor wavelet decomposition [4] is first performed and we compute the features for each Gabor filter output afterwards. Following this approach we obtain a 16-dimensional vector to represent the texture information for each image (Fig. 5).

Table 2
Detailed information of synthetic dataset.

Classes	Mean	Covariance
1	$[0, -3]$	$[1, 0; 0, 1.5]$
2	$[0, -4]$	$[1, 0; 0, 1.5]$
3	$[0, -5]$	$[1, 0; 0, 1.5]$
4	$[1, -1]$	$[1, 0; 0, 1.5]$
5	$[-1, 1]$	$[1, 0; 0, 1.5]$
6	$[-2, 0]$	$[1, 0; 0, 1.5]$
7	$[2, 0]$	$[1, 0; 0, 1.5]$
8	$[1, 0]$	$[1, 0; 0, 1.5]$
9	$[0, 1]$	$[1, 0; 0, 1.5]$
10 (relevant class)	$[0, 5]$	$[1.5, 0; 0, 1.5]$

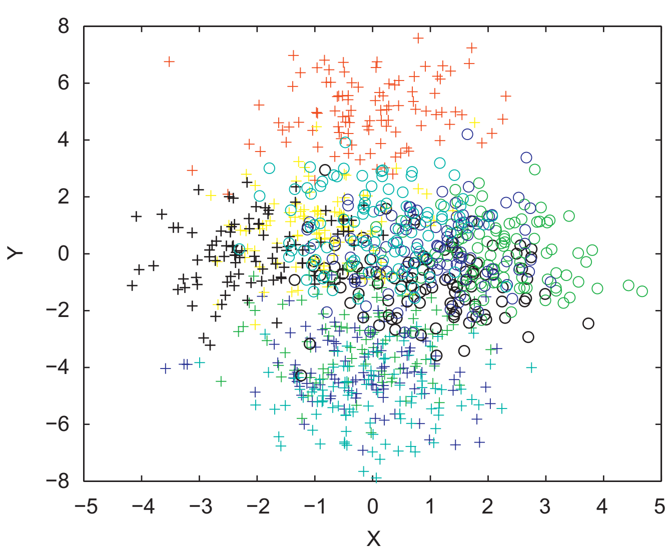

Fig. 4. Visualization of the synthetic dataset. Relevant class: red plus; irrelevant class: others. In the experiments, we use one versus all strategy for the multi-class classification problem. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Performance evaluation

4.2.1. Results on synthetic dataset

In our experiments, a category is first picked from the dataset randomly, and this category is assumed to be the user's desired query target. The framework then improves retrieval results by user's feedback. During each iteration of the relevance feedback procedure, 10 instances are picked from the dataset and labelled as either relevant or irrelevant samples based on the ground truth of the dataset. For the first iteration, three positive and seven negative samples are randomly picked out and the three learning schemes are applied with this initial set. For the iterations afterward, each model selects 10 samples and the number of the samples in the positive and negative regions are recorded.

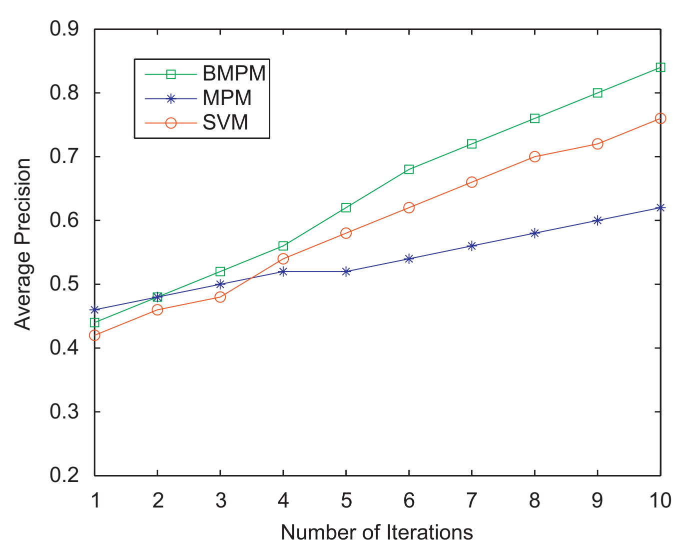

Fig. 6. The experimental results for three models on the synthetic dataset: top-50 returned samples are evaluated.

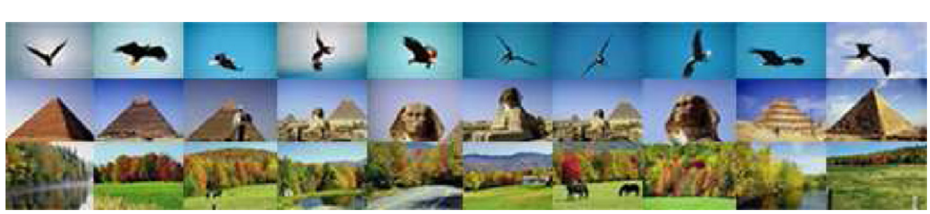

Fig. 5. Example images from COREL image database.

The precision of each model is then computed. Fig. 6 shows the evaluation results of top-50 returned results. We observe that BMPM outperforms the other models. The SVM-based approach achieves better performance than the one of MPM in the application of relevance feedback in CBIR.

4.2.2. *Results on real-world dataset*

In the following, we present the experimental results by the algorithms on real-world images. The metric of evaluation is the *average precision* which is defined as the average ratio of the number of relevant images in the returned images over the total number of the returned images.

In the real-world dataset experiments, the iteration is similar as the one of synthetic dataset, except that we need to first perform feature extraction for the query images and image database. In each iteration of the feedback process, 10 images are picked from the database and labelled as either relevant or irrelevant based on the ground truth of the database. The precision is then recorded, and the whole process is repeated for 10 times to produce the average precision in each iteration for the proposed method.

Fig. 7 shows the evaluation results on the 6-Bird dataset. From the results on the real-world dataset, we observe that our proposed BMPM-based methodology outperforms other approaches such as MPM and SVM. We also notice that the performance of SVM is very competitive to BMPM, and MPM achieves the worst performance in these three models. The reason is that MPM cannot model the relevance feedback problem as good as SVM and BMPM due to its assumption that both positive and negative feedbacks are equal. From here we can see how the bias works. In order to know the detailed comparison of the three methods after a set number of iterations, we list the retrieval results in Tables 3 and 4. From the results, we can also see the similar results which verify our hypothesis.

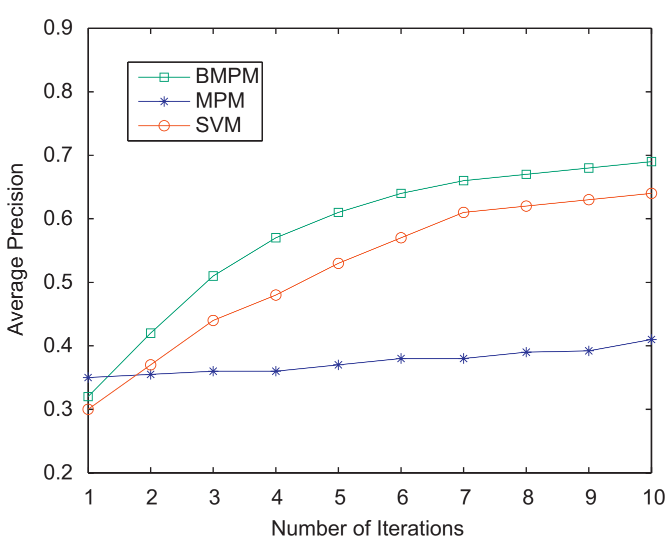

Fig. 7. The experimental results for three models on the 6-Bird dataset: top-50 returned images are evaluated.

Table 3
Number of relevant images in top-50 returned images.

Learning models	Number of iterations				
	0	1	3	7	10
BMPM	5	12	16	**26** ↑	**33** ↑
MPM	5	13	16	18	21
SVM	5	11	14	23	29

Table 4
Average precision after 10 iterations.

Learning models	Top-50 at 6-Bird	Top-30 at 6-Bird	Top-20 at 6-Bird
BMPM	**0.68** ↑	**0.71** ↑	**0.75** ↑
MPM	0.42	0.47	0.55
SVM	0.63	0.66	0.70

4.3. *Discussions*

We have observed that the proposed BMPM-based scheme performs better than the conventional approaches from the experimental results. The traditional classification approaches, such as regular SVM and MPM, without considering the bias in the retrieval tasks is not appropriate in solving the relevance feedback problem. Furthermore, we know there are other methods to address the imbalanced dataset problem in literature [3,19]. We can also consider to include them in our scheme in the future. Nevertheless, we have observed the promising results in demonstrating the effectiveness of our proposed BMPM technique for the relevance feedback problem in image retrieval.

5. Conclusion and future work

In this paper, we address the problem of imbalanced classification needed with the relevance feedback in CBIR and present a novel learning framework, the BMPM-based approach, to treat this problem more precisely. In contrast to the traditional methods, the BMPM directly controls the worst-case classification accuracy in order to impose a certain bias in favor of the relevant images. This provides a more effective way to handle imbalanced classification problems. We evaluate the performance of the BMPM-based relevance feedback on the synthetic dataset and the COREL image dataset. The results on both datasets show that the BMPM outperforms the other learning models on the problem of relevance feedback.

Although we could observe that our proposed learning framework is more precise than other state-of-art techniques, in some pattern recognition tasks, especially in information retrieval, effectiveness is sometimes more important than efficiency, in which expensive time-cost presents one of the main bottlenecks of the BMPM learning model. To solve such problem, a possible direction is to propose other methods to solve this optimization problem. Undoubtedly, a new learning scheme for image retrieval will be still a highly active research topic in the future.

References

[1] C.-H. Chan, K.-C. Sia, I. King, Utilizing inter- and intra-query relevance feedback for content-based image retrieval, in: Proceedings of the International Conference on Neural Information Processing (ICONIP2003), Istanbul, Turkey, 2003.

[2] I.J. Cox, M.L. Miller, T.P. Minka, P.N. Yianilos, An optimized interaction strategy for Bayesian relevance feedback, in: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR'98), Santa Barbara, USA, 1998, pp. 553–558.

[3] A. Estabrooks, T. Jo, N. Japkowicz, A multiple resampling method for learning from imbalanced data sets, Computational Intelligence 20 (1) (2004) 18–36.

[4] J. Fiser, I. King, Gabor-wavelet decomposition based filtering of gray-level images for object recognition experiments, Spatial Vision 11 (1) (1998) 117–119.

[5] C.H. Hoi, C.H. Chan, K. Huang, M.R. Lyu, I. King, Biased support vector machine for relevance feedback in image retrieval, in: Proceedings of International Joint Conference on Neural Networks (IJCNN2004), Budapest, Hungary, July 2004, pp. 3189–3194.

[6] S.C. Hoi, M.R. Lyu, R. Jin, A unified log-based relevance feedback scheme for image retrieval, IEEE Transactions on Knowledge and Data Engineering 15 (4) (2006) 509–524.
[7] P. Hong, Q. Tian, T.S. Huang, Incorporate support vector machines to content-based image retrieval with relevance feedback, in: Proceedings of IEEE International Conference on Image Processing (ICIP2000), Vancouver, BC, Canada, October 2000, pp. 750–753.
[8] K. Huang, H. Yang, I. King, M. Lyu, L. Chan, The minimum error minimax probability machine, Journal of Machine Learning Research 5 (2004) 1253–1286.
[9] A.K. Jain, A. Vailaya, Shape-based retrieval: a case study with trademark image database, Pattern Recognition 9 (1998) 1369–1390.
[10] Z. Jin, I. King, X. Li, Content-based image retrieval by relevance feedback, in: Proceedings of the Fourth International Conference on Visual Information Systems (VISUAL2000), Lyon, France, 2000.
[11] I. King, Z. Jin, Relevance feedback content-based image retrieval using query distribution estimation based on maximum entropy principle, in: Proceedings of the International Conference on Neural Information Processing (ICONIP2001), Shanghai, China, 2001.
[12] G. Lanckriet, L.E. Ghaoui, C. Bhattacharyya, Minimax probability machine, in: Advances in Neural Information Processing Systems 14 (NIPS14), Vancouver, BC, Canada, 2001, pp. 801–807.
[13] G. Lanckriet, L.E. Ghaoui, C. Bhattacharyya, M. Jordan, A robust minimax approach to classification, Journal of Machine Learning Research 3 (2003) 555–582.
[14] Y. Rui, T.S. Huang, M. Ortega, S. Mehrotra, Content-based image retrieval with relevance feedback in MARS, in: Proceedings of IEEE International Conference on Image Processing (ICIP'97), Washington, DC, USA, October 1997, pp. 815–818.
[15] Y. Rui, T.S. Huang, M. Ortega, S. Mehrotra, Relevance feedback: a power tool in interactive content-based image retrieval, IEEE Transactions on Circuits and Systems for Video Technology 8 (5) (1998) 644–655.
[16] K.C. Sia, I. King, Relevance feedback based on parameter estimation of target distribution, in: Proceedings of the International Joint Conference on Neural Networks (IJCNN2002), vol. 2, Honolulu, HI, USA, 2002, pp. 1974–1979.
[17] A. Smeulders, M. Worring, S. Santini, A. Gupta, R. Jain, Content-based image retrieval at the end of the early years, IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (12) (2000) 1349–1380.
[18] J. Smith, S.F. Chang, Automated image retrieval using color and texture, Technical Report, Columbia University, 1995.
[19] G. Wu, E.Y. Chang, KBA: kernel boundary alignment considering imbalanced data distribution, IEEE Transactions on Knowledge and Data Engineering 17 (6) (2005) 786–795.

Xiang Peng received his BS degree in Computer Science and Technology from South China University of Technology, Guangzhou, China, in 2005. He currently works as a graduate student in the Department of Computer Science and Engineering in The Chinese University of Hong Kong, Shatin, N.T., Hong Kong. His research interests include information retrieval, machine learning and pattern recognition.

Irwin King received the BSc degree in Engineering and Applied Science from California Institute of Technology, Pasadena, in 1984. He received his MSc and PhD degrees in Computer Science from the University of Southern California, Los Angeles, in 1988 and 1993, respectively. While working on his degree, he worked as a Scientific Software Engineer at the Xerox Special Information System (XSIS) group in Pasadena. At Xerox, he helped to design and implement the Analyst System, which is an all-in-one software package with seamless integration of word processing, spreadsheet computation and charting, painting, drawing, and database management. Aside from working at Xerox, he also taught various undergraduate courses in Computer Science at the Occidental College, Los Angeles.

He joined the Chinese University of Hong Kong in 1993. His research interests include machine learning, multimedia processing, and web intelligence.

He is a member of ACM, IEEE Computer Society, International Neural Network Society (INNS), and Asian Pacific Neural Network Assembly (APNNA). Currently, he is serving the Neural Network Technical Committee (NNTC) under the IEEE Computational Intelligence Society (formerly the IEEE Neural Network Society). He is also a governing board member of the Asian Pacific Neural Network Assembly (APNNA). He is a founding member of the Neural Computing and Engineering Laboratory (NCEL) and the Multimedia Information Processing Laboratory (MIP Lab). He is a member of the Editorial Board of the Neural Information Processing-Letters and Reviews Journal (NIP-LR). He has served as program and/or organizing member in international conferences and workshops, e.g., WWW, ICASSP, IJCANN, ICONIP, etc. He has also served as reviewer for international conferences as well as journals, e.g., Information Fusion, IEEE TCAS, SIGMOD, IEEE Transactions on Neural Networks, IEEE Pattern Analysis and Machine Intelligence, IEEE Transactions on Multimedia, IEEE Transactions on Knowledge and Data Engineering, IEEE Transactions on System, Man, and Cybernetics, Machine Vision and Applications, International Journal of Computer Vision, Real-Time Imaging, SPIE Journal of Electronic Imaging, International Journal of Pattern Recognition and Artificial Intelligence, etc.