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Semi supervised Inclined Maximum Confine Analysis for Convertible Image Reclamation

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***Abstract*— with many impending realistic applications, content-based image reclamation (CBIR) has fascinated substantial awareness all through the past few years. A assortment of significance feedback (SF) schemes have been residential as a prevailing tool to bridge the semantic gap stuck between low-level visual features and high-level semantic concepts, and thus to improve the recital of CBIR systems. Among diverse SF approaches, support-vector-machine (SVM)-based SF is one of the nearly everyone admired techniques in CBIR. Despite the accomplishment, unswervingly using SVM as an SF scheme has two main drawbacks. First, it treats the affirmative and pessimistic feedbacks uniformly, which is not apposite since the two groups of guidance feedbacks have dissimilar properties. Second, mainly of the SVM-based SF techniques do not acquire into description the unlabeled samples, although they are very accommodating in constructing a fine classifier.**

To survey solutions to trounce these two drawbacks, in this manuscript, we recommend a Inclined maximum confine analysis (IMCA) and a semisupervised IMCA (Semi IMCA) for integrating the discrete properties of feedbacks and utilizing the information of unlabeled samples for SVM-based SF schemes.

The IMCA differentiates constructive feedbacks from unconstructive ones based on confined scrutiny, whereas the SemiIMCA can efficiently incorporate information of unlabeled samples by introducing a Laplacian regularizer to the IMCA. We properly formulate this predicament into a broad subspace erudition assignment and then recommend an habitual approach of formative the dimensionality of the embed subspace for SF. Extensive experiments on a huge real-world image database exhibit that the proposed proposal pooled with the SVM SF can appreciably improve the recital of CBIR systems.

Keywords- **Content-based image reclamation (CBIR), graph embedding, significance feedback (SF), support vector machine (SVM).**

I. INTRODUCTION

During the past few years, content-based image repossession (CBIR) has gained much attentiveness for its potential applications in multimedia organization.It is provoked by the explosive growth of image proceedings and the online user-friendliness of distantly stored images. An effective search scheme is urgently necessary to administer the huge image folder.

Different from the customary search engine, in CBIR, an image query is described by by means of one or more pattern images, and low-level visual features are mechanically extracted to represent the images in the database. However, the low-level features captured from the images possibly will not precisely characterize the high-level semantic concepts. To narrow down the so-called semantic gap, relevance feedback (SF) was introduced as a commanding tool to augment the pesformance of CBIR. Huang et al. introduced both the query pressure group and the reweighting techniques

A self-organizing map was used to make the SF algorithms. In, one-class maintain vector machine (SVM) predictable the density of constructive feedback samples. Derived from one-class SVM, a biased SVM present at birth the merits of one-class SVM but included the unconstructive feedback samples. Allowing for the geometry organization of image low-level visual features, planned manifold-learning-based approaches to find the essential structure of images and improve the repossession presentation. With the surveillance that "all positive examples are alike; each unconstructive example is negative in its own way," SF was formulated as a biased subspace education problem, in which there is an unknown numeral of classes, but the user is only anxious about the positive class.

However, all of these methods have some boundaries. For example, the method in is heuristically based, the compactness judgment method in ignores any in sequence contained in the unhelpful feedback samples, and the discriminate subspace education techniques in often suffer from the so-called "small model size" problem. Regarding the positive and negative feedbacks as two dissimilar groups, classification- based SFs have become a accepted technique in the CBIR the public. However, SF is very diverse from the traditional organization problem since the feedbacks provided by the customer are often impesfect in real-world image repossession systems.

Therefore, small sample education methods are most talented for SF. Two-class SVM is one of the popular small sample education methods widely used in current years and obtains the state-ofthe- art presentation in organization for its good simplification ability The SVM can realize a negligible structural risk by minimizing the Vapnik–Chervonenkis scope Guo et al. urbanized a unnatural comparison measure for image Reclamation , which learns a border line that divides the images into two groups, and samples inside the border line are ranked by their Euclidean aloofness to the query image. The SVM active learning process selects samples lock to the border line as the most revealing samples for the user to label . Random example techniques were functional to assuage unstable, biased, and over fitting troubles in SVM SF. Li et al. proposed a Multitraining SVM method by adapting a co-

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training technique and a random example method. Nevertheless, most of the SVM SF approaches take no notice of the basic dissimilarity between the two different groups of feedbacks, i.e., all positive feedbacks share a comparable perception while each unconstructive feedback usually varies with dissimilar concepts.

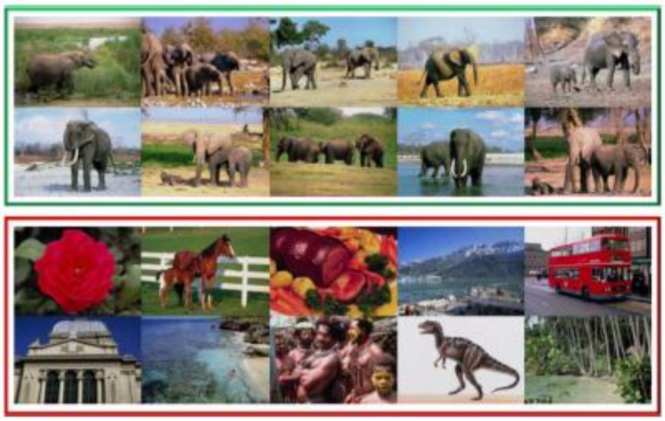

Figure 1: Typical set of positive- and negative-feedback samples in an SF Iteration.

For instance, a archetypal set of feedback samples in SF iteration is shown in Fig. 1. All the samples labeled as constructive feedbacks share a common notion (i.e., elephant), while each example labeled as unconstructive feedback varies with miscellaneous concepts (i.e., flower, horse, banquet, hill, etc.). Traditional SVMSF techniques treat constructive and unconstructive feedbacks equally . Directly by means of SVM as an SF scheme is potentially destructive to the presentation of CBIR systems.

One problem stems from the information that different semantic concepts live in diverse subspaces and each image can live in a lot of poles apart subspaces, and it is the goal of SF schemes to figure out "which one". However, it will be a weight for traditional SVM-based SF schemes to adjust the domestic Parameters to get a feel for to the changes of the subspace. Such difficulties have severely tainted the good organization of conventional SVM SF approaches for CBIR. Additionally, it is challenging to add in the information of unlabeled samples into established SVM-based SF schemes for CBIR, although unlabeled Samples are very obliging in constructing the optimal classifier, Alleviating sound and enhancing the presentation of the system.

To explore solutions to these two above mentioned predicament in the current knowledge, we recommend a biased maximum margin analysis (IMCA)and a semi supervised IMCA(SemiIMCA) for the conformist SVM SF schemes, based on the graph-embedding framework. The proposed scheme is mainly based on the following: 1) the efficiency of treating constructive examples and unconstructive examples unequally 2) the implication of the optimal subspace or characteristic subset in interactive CBIR; 3) the success of diagram embedding in characterizing intrinsic geometric properties of the data set in high-dimensional space; and 4) the expediency of the graph-embedding framework in constructing semisupervised learning techniques. With the incorporation ofIMCA, labeled positive feedbacks are mapped as close as possible, whereas labeled unconstructive feedbacks are separated from labeled constructive feedbacks by a maximum margin in the summary subspace.

The traditional SVM combined with IMCA can better model the SF procedure and reduce the pesformance dilapidation caused by distinct properties of the two groups of feedbacks. The SemiIMCA can incorporate the in sequence of unlabeled samples into the SF and effectively alleviate the ovesfitting problem caused by the small size of labeled preparation samples. To show the efficiency of the proposed method combined with the SVM SF, we will compare it with the conventional SVM SF and some other applicable existing techniques for SF on a real-world image compilation. Experimental results exhibit that the planned scheme can significantly improve the presentation of the SVMSF for image Reclamation.

The rest of this paper is prearranged as follows: In Section II, the related preceding work, i.e., the principle of SVM SF for CBIR and the graph-embedding framework, are for a short time review. In Section III, we pioneer the IMCA and the SemiIMCA for SVM SF. An image repossession system is given in Section IV. A large numeral of experiments that validate the efficiency of the planned scheme are given in Section V. Conclusion and future work are presented in Section VI.

II. RELATED PREVIOUS WORK

A. Principle of SVM SF for CBIR

Here, we briefly introduce the standard of the conventional SVM-based SF for CBIR. The SVM equipment the structure risk minimization by minimizing Vapnik–Chervonenkis magnitude Consider a linearly separable double organization problem as follows:

$$\{(x_1, y_1), \ldots, (x_N, y_N)\} \text{ and } y_{i=1,\ldots,N} = \{+1, -1\} \tag{1}$$

Where x_i denotes a h-dimensional vector, N is the numeral of training samples and y_i is the sticker of the class that the vector belongs to. The objective meaning of SVM aims to find an most favorable hyper plane to disconnect the two classes, i.e.,

$$w^T x + b = 0 \tag{2}$$

where x is an input vector, w is a heaviness vector, and is a bias. SVM attempts to find the two parameters w and b for the most favorable hyper plane by maximizing the geometric border ,

$$y_i(w^T x_i + b) \geq 1 \tag{3}$$

The solution of the purpose function can be originate through a Wolf dual difficulty with the Lagrangian multiplied by α_i, i.e.,

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)/2 \quad (4)$$

In general, in the dual problem, data points appear only in the inner produce, which can be often replaced by a positive distinct kernel function for better concert, i.e.,

$$x_i \cdot x_j \rightarrow \Phi(x_i) \cdot \Phi(x_j) = K(x_i, x_j) \quad (5)$$

where K (.) is a kernel function. The kernel version of theWolfe dual problem is

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j K(x_i \cdot x_j)/2. \quad (6)$$

Thus, for a given kernel function, the SVM classifier is given By

$$F(x) = \mathrm{sgn}\,(f(x)) \quad (7)$$

B. Graph-Embedding Framework

In order to describe our proposed approach clearly,we first review the graph-embedding framework introduced in [30]. Generally, for a classification problem, the sample set can be represented as matrix , where indicates the total number of the samples and is the feature dimensionality.

$$L = D - W \qquad D_{ii} = \sum_{j \neq i} W_{ij} \qquad \forall i = 1, \ldots, n. \quad (8)$$

Then, the similarities among vertex pairs can be maintained according to the graph-preserving criterion as follows:

$$y^* = \underset{\mathrm{tr}(YBY^T)=c}{\arg\min} \sum_{i \neq j} \|y_i - y_j\|^2 W_{ij} = \underset{\mathrm{tr}(YBY^T)=c}{\arg\min} \; \mathrm{tr}(YLY^T) \quad (9)$$

$$L^p = D^p - W^p \qquad D^p_{ii} = \sum_{j \neq i} W^p_{ij} \qquad \forall i = 1, \ldots, n \quad (10)$$

In , based on the graph-embedding framework, (9) can be resolved by converting it into the following trace ratio formulation:

$$Y^* = \arg\min_{Y} \frac{\mathrm{tr}(YLY^T)}{\mathrm{tr}(YBY^T)}. \quad (11)$$

$$\alpha^* = \arg\min_{\alpha} \frac{\mathrm{tr}(\alpha^T XLX^T \alpha)}{\mathrm{tr}(\alpha^T XBX^T \alpha)}. \quad (12)$$

III. IMCA AND SEMI IMCA FOR SVM SF IN CBIR

With the scrutiny that *"all constructive examples are alike; each negative example is unconstructive in its own way*," the two groups of feedbacks have different property for CBIR. However, the traditional SVM SF treats the constructive and unconstructive feedbacks uniformly. To alleviate the pesformance dreadful conditions when using SVM as an SF scheme for CBIR, we travel around solutions based on the disagreement that dissimilar semantic concepts lie in dissimilar subspaces and each representation can lie in many dissimilar thought subspaces.

We formally formulate this problem into a wide-ranging subspace erudition trouble and propose a IMCA for the SVM SF scheme. In the summary subspace, the unconstructive feedbacks, which differ in assorted concept with the question sample, are estranged by a maximum margin from the constructive feedbacks, which share a similar concept with the query sample. Therefore, we can easily map the constructive and unconstructive feedbacks onto a semantic subspace in agreement with human awareness of the image inside. To make use of the information of unlabeled samples in the database, we introduced a Laplacian regularizer to the IMCA, which will lead to partially IMCA for the SVM SF. The resultant Laplacian regularize is largely based on the notion of local steadiness, which was enthused by the freshly emerging multiple learning the public and can successfully depict the weak comparison relationship between unlabeled samples pairs. Then, the outstanding images in the database are probable onto this ensuing semantic subspace, and a similarity compute is applied to sort the images based on the new representations.

For the SVM based SFs, the remoteness to the hyper plane of the classifier is the principle to distinguish the query-relevant samples beginning the query-irrelevant samples. After the protuberance step, all positive feedbacks are clustered together, while unconstructive feedbacks are well estranged from positive feedbacks by a greatest border. Therefore, the resulting SVM classifier hyper plane in this subspace will be much simpler and enhanced than that in the innovative high-dimensional attribute space. Different from the classical subspace learning methods, e.g., principal constituent analysis and linear discriminate analysis (LDA), which can only see the linear global Euclidean organization of samples, IMCA aims to learn a projection matrix such that, in the predictable space, the positive samples have high local within-class resemblance but the sampleswith dissimilar labels have high limited between-class separability. To portray the algorithm clearly, we first commence some notations of this move toward.

$$\begin{aligned} \tilde{S}_I &= \sum_{i} \sum_{j: j \in \mathbb{N}_i^s \ or \ i \in \mathbb{N}_j^s} \|\alpha^T x_i - \alpha^T x_j\|^2 * W_{ij} \\ &= 2\,\mathrm{tr}\left[\alpha^T X(D - W)X^T \alpha\right] \end{aligned} \quad (13)$$

$$W_{ij} = \begin{cases} 1/|\mathbb{N}^s|, & \text{if } l(i) = 1 \text{ and } l(j) = 1, i \in \mathbb{N}_j^s \text{ or } j \in \mathbb{N}_i^s \\ 0, & \text{else} \end{cases} \quad (14)$$

For the punishment graph G^p , its correspondence matrix W_{ij} represents geometric or statistical properties to be avoided and is worn as a constriction prevailing conditions in the graph-embedding framework. In the IMCA, the sentence graph G^p is constructed to represent the local separability connecting the constructive and pessimistic program. More stringently dialogue, we be expecting that the total average periphery between the illustration pairs with different labels must be as large as possible.

For each feedback sample, we find its neighbor feedbacks K_2 with different labels and put edges between corresponding pairs of feedback samples with weights W_{ij}^{p}. Then, the penalty graph can be formed as follows:

$$\begin{aligned}\tilde{S}_p &= \sum_i \sum_{j: j\in \mathbb{N}_i^p \ or \ i\in \mathbb{N}_j^p} \|\alpha^T x_i - \alpha^T x_j\|^2 * W_{ij}^p \\ &= 2\mathrm{tr}\left[\alpha^T X(D^p - W^p)X^T\alpha\right] \qquad (15)\end{aligned}$$

$$W_{ij}^p = \begin{cases} 1/|\mathbb{N}^p|, & \text{if } l(i)=1 \text{ and } l(j)=-1, i\in \mathbb{N}_j^p \text{ or } j\in \mathbb{N}_i^p \\ 0, & \text{else} \end{cases} \qquad (16)$$

In the following, we describe how to utilize the graph-embedding framework to develop algorithms based on the designed intrinsic and penalty graphs. Different from the original formulation of the graph-embedding framework in [30], the IMCA algorithm optimizes the objective function in a trace difference form instead, i.e.,

$$\begin{aligned}\alpha^* &= \arg\max_\alpha 2\mathrm{tr}\left[\alpha^T X(D^p - W^p)X^T\alpha\right] \\ &\quad - 2\mathrm{tr}\left[\alpha^T X(D - W)X^T\alpha\right] \\ &= \arg\max_\alpha \mathrm{tr}\left[\alpha^T X(D^p - W^p)X^T\alpha\right] \\ &\quad - \mathrm{tr}\left[\alpha^T X(D - W)X^T\alpha\right] \\ &= \arg\max_\alpha \mathrm{tr}(\alpha^T XBX^T\alpha) - \mathrm{tr}(\alpha^T XLX^T\alpha) \\ &= \arg\max_\alpha \mathrm{tr}\left[\alpha^T X(B-L)X^T\alpha\right]. \qquad (17)\end{aligned}$$

Without prior information on data distributions, IMCA can find more reliable low-dimensional representations of the data compared with MMC [38] and also follow the original assumption in biased discriminant analysis (BDA) [20] (i.e., all positive examples are alike; each negative example is negative in its own way). It should be noted that previous methods [39], [40] that followed MMC cannot be directly used for the SVM SF in image Reclamation because these methods treat samples in different classes equally.

$$\max_\alpha \mathrm{tr}\left(\alpha^T X(B-L)X^T\alpha\right) = \sum_{k=1}^{l} \alpha_k^T X(B-L)X^T\alpha_k$$
$$s.t.\ \alpha_k^T\alpha_k - 1 = 0, \quad k = 1, 2, \ldots, l. \qquad (18)$$

The motivation for introducing this term is inspired by the regularization principle, which is the key to enhancing the generalization and the robust pesformance of the approach in practical applications. There are a lot of possible ways to choose a regularizer for the proposed IMCA. In this paper, we chose the Laplacian regularizer, which is largely inspired by the recently emerging manifold learning community. This scheme can preserve weak (probably correct) similarities between all unlabeled sample pairs and thus effectively integrate the similarity information of unlabeled samples into IMCA. By integrating the Laplacian regularizer into the supervised IMCA, we can easily obtain SemiIMCA for the SVM SF, i.e.,

$$\alpha^* = \arg\max_\alpha \mathrm{tr}\left[\alpha^T X(B - L - \beta * U)X^T\alpha\right]$$

IV. CBIR System

In experiments, we use a separation of the Corel Photo veranda as the test information to appraise the presentation of the planned scheme. The original Corel Photo Gallery includes plenty of semantic categories, each of which contain 100 or more descriptions. However, some of the categories are not suitable for representation Reclamation since some images with different concepts are in the same category and many images with the same concept are in different categories. Therefore, the existing categories in the innovative Corel Photo Gallery are unobserved and reorganized into 80 conceptual lessons based on the ground truth, such as lion,

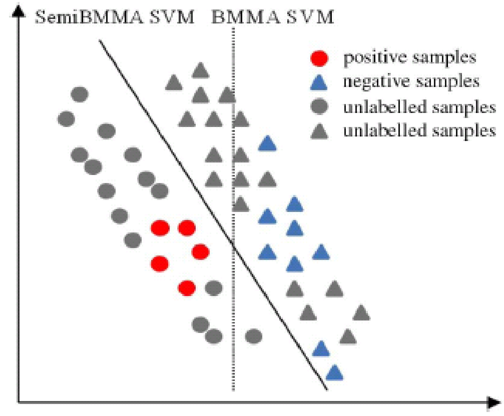

Figure 2: Illustration of the SVM hyperplane comparison between IMCA SVM and SemiIMCA SVM for two classes of feedbacks

Castle, aviation, train, dog, autumn, cloud, and tiger. Finally, the test folder is comprised of totally 10 763 real-world descriptions. Given a query representation by the user, the CBIR system is probable to feed back more semantically applicable descriptions after each feedback iteration. However, during SF, the numeral of the applicable images is usually very small since of the semantic gap.

At the same time, the client would not like to label a large numeral of samples. The user also expects to get hold of more relevant descriptions with only a few rounds of SF iterations. Keeping the size of labeled pertinent images small and observance the SF iterations few are two key issues in conniving the image repossession system. Therefore, we devise the subsequent CBIR framework for that reason to evaluate the SF algorithms. we can notice that, when a question image is provided by the customer, the image repossession system first extracts the low-level skin tone. Then, all the images in the database are sorted based on a comparison metric, i.e., Euclidean detachment. If the user is pleased with the results, the repossession process is ended, and the consequences are accessible to the customer. However, because of the semantic gap, most of the time, the user is not pleased with the first repossession results. Then, she/he will label the most semantically applicable images as positive feedbacks in top repossession consequences. All of the remaining images in top results are automatically labeled by the organization as the unconstructive feedbacks. Based on the small-size positive and negative feedbacks, the SF model can be skilled based on an assortment of existing technique. Then, all the images in the folder are resorted based on a new comparison metric. After each round of Reclamation, the user will check whether the consequences are pleased. If the user is pleased with the results, then the development is ended;

otherwise, the feedback development repeats until the user is pleased with the repossession results. Generally, the image depiction is a crucial problem in CBIR. The images are typically represent by low-level features, such as color, touch, and shape, each of which can detain the content of an image to a quantity of extent.

V. EXPERIMENTAL RESULTS ON A REAL-WORLD IMAGE DATABASE

A. *Intrinsic Problems in Traditional Two-Class SVM SF*

A picture is usually represent as a high-dimensional characteristic vector in CBIR. However, one key matter in SF is regarding which division of skin tone can imitate the basic property of different groups of feedback samples and advantage the building of the optimal classifier. This problem can be illustrated from some real-world statistics in SF. There are five constructive samples and five unconstructive feedback samples. We haphazardly select two skin tone to construct the most favorable SVM hyper plane for three times. As shown in we can see that the resulting SVM classifiers are miscellaneous with different combination of features.

It is essential to obtain a satisfactory classifier when the figure of available feedback samples is small, which is for all time the case in SF, mainly in the first few rounds of feedbacks. Therefore, we first show a straightforward example to imitate the unstable problem of SVM when commerce with a small number of preparation samples. The open circles in Fig. 6 indicate the positive feedback samples, and the plus points indicate the unconstructive samples in the SF. it shows an optimal hyper plane, which is trained by the original training samples and it shows a dissimilar optimal hyper plane, which are trained by the original training set with only one and two incremental optimistic samples, in that order. From Fig. 6, we can see that the hyper plane of the SVM classifier piercingly changes when a new incremental sample is incorporated into the innovative training set. Additionally, we can also message that the optimal hyper planes of SVM are much compound when the feedbacks have a difficult allocation.

Note that the comparable results have been indicated in the preceding research. However, here, we have shown to some extent different troubles in the conventional SVMSF, that is, distinct belongings of advice samples in SF and uneven and compound hyper planes of the conventional SVM in the first few rounds of feedbacks.

B. *Features Extraction Based on Different Methods*

Six experiments are conducted for compare the IMCA with the traditional LDA, the BDA process and a graph-embedding come up to, i.e., MFA, in verdict the most discriminative information. We plot the directions that communicate to the principal eigen value of the decaying matrices for LDA, BDA, MFA, and IMCA, in that order. From these examples, we can clearly notice that LDA can find the best discriminative course when the data from each class are disseminated as Gaussian with comparable covariance matrices

Prejudiced toward the positive samples, BDA can find the course that the optimistic samples are well estranged with the unconstructive samples when the constructive samples have a Gaussian allocation, but it may also perplex when the allocation of the constructive samples is more difficult. For instance, in Fig. 7(b), BDA can find the way for personal constructive samples from unconstructive ones.

C. *Statistical Experimental Results*

Here, we evaluate the presentation of the planned scheme on a real-world representation database. We use precision–scope curve, exactitude rate, and standard departure to appraise the efficacy of the image repossession algorithms. The scope is specified by numeral of top-ranked descriptions accessible to the user. The exactitude is the major estimate principle, which evaluates the efficiency of the algorithms. The precision–scope curve describes the precision with various scopes and can give the overall recital evaluation of the approach. The precision rate is the ratio of the figure of relevant descriptions retrieved to the top retrieved images, which emphasizes the exactitude at a meticulous value of scope. Standard departure describes the stability of dissimilar algorithms. Therefore, the exactitude evaluates the efficacy of a given algorithm, and the equivalent standard departure evaluates the sturdiness of the algorithm. We empirically select parameters and according to manifold education approaches. Bearing in mind the assessable efficiency, we randomly select 300 unlabeled samples in every one round of feedback iteration. For the tradeoff parameter among labeled samples and unlabeled samples, we simply set $\beta=1$. For all the SVM based algorithms, we choose the Gaussian kernel, i.e.,

$$K(x,y) = e^{-\rho|x-y|^2}, \qquad \rho = 0.001.$$

Note that, the kernel parameters and the kernel type can appreciably affect the recital of Reclamation. For dissimilar image database, we be supposed to tune the kernel parameters and the kernel type vigilantly. In our experiments, we determine the kernel parameters from a succession of values according to the presentation. Moreover, much better pesformance can be achieve by alteration the kernel parameters additional for dissimilar queries

Figure 3: **Example categories used in the small-size image database**

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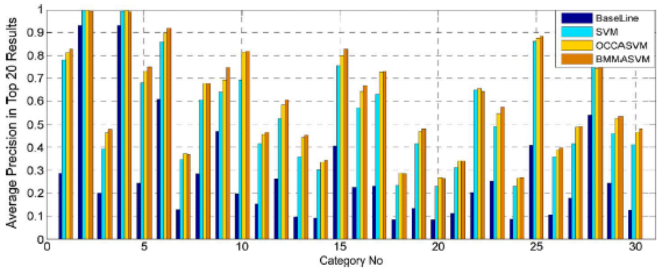

Figure 4: **Average precisions in the top 20 results of SVM, OCCA SVM, and IMCA SVM after two rounds of feedback**

VI. CONCLUSION AND FUTURE WORK

SVM based SF has been extensively used to viaduct the semantic gap and enhances the presentation of CBIR system. However, directly using SVM as an SF scheme has two main drawbacks. First, it treats the optimistic and unconstructive feedbacks equally, although this supposition is not suitable since all constructive feedbacks share a widespread concept, while each unconstructive feedback differ in diverse concepts. Second, it does not take into account the unlabeled samples, although they are incredibly helpful in constructing a good classifier.

In this paper, we have explore solutions based on the disagreement that dissimilar semantic concept live in dissimilar subspaces and each reflection can live in many dissimilar subspaces. We have designed IMCA and SemiIMCA to alleviate the two drawbacks in the usual SVM SF. The novel approach can differentiate the optimistic feedbacks and the unconstructive feedbacks by maximizing the local border and integrate the in sequence of the unlabeled samples by introducing a Laplacian regularizer. Extensive experiments on a large real-world Corel picture database have revealed that the planned scheme mutual with the conventional SVM SF can appreciably improve the concert of CBIR systems. Despite the promising results, more than a few questions remain to be investigated in our future work. First, this approach involve dense-matrix eigen putrefaction, which can be computationally expensive both in time and memory. Therefore, an effective technique for working out is obligatory to alleviate the drawback. Second, theoretic questions need to be investigate on the subject of how the projected scheme affects the simplification error of organization models. More specifically, we expect to get a better exchange between the incorporation of the different properties of feedbacks and the simplification error of the classifier

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