Multiple Kernel Learning for Image Contour Extraction

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Abstract—**Nowadays, it rapidly increases that digital image information that stored locally or on internet, it has been an important issue that how to save and retrieve images in an effective way. Traditional manual classification can't meet the actual needs. Now the method commonly used is to extract the image contour, it does not use the full image to deal with the image effectively. Currently, the efficiency of many traditional image contour extraction methods are low for large-scale, heterogeneous digital image, and the result is always poor. For example, the gradient-based method is suitable for straight contour, and the method of prior knowledge drops into the local extreme value easily. According to this, this paper presents an image contour extraction method based on multiple kernels learning (MKL). The method adopts multiple kernels to construct a framework for learning classifier, and then it uses the accumulation of learning classifier and regulates the probability of the output, then it can improve the test results by operator. The experimental results show that this method for contour extraction is more effective. In terms of number, size and accuracy of data collection, this method is much closer to human intuitive initial conditions comparing with other methods, and better effect**

Index Terms—**Digital Information; Contour Extraction; Multiple Kernel Learning**

I. INTRODUCTION

Computer and internet technology is now popular rapidly, the number of digital images stored in local or network is growing at a geometric rate, how to find the image that the user needs from the massive image database quickly becomes more and more urgent. A reasonable and easy-to-implement approach is to extract the outline of the image and using it as a representative of the entire image. At the time of retrieval, the user can quickly browse and query and it can meet the demand of rapid extraction of information. At present, it has a relatively wide range of applications in the field of aeronautical engineering, industrial manufacturing and medical imaging. For example, in the hospital, they should deal with a large number of CT images, PET images, and fluoroscopy and X optical image every day. Making a classification of medical images is not only beneficial to the treatment and case studies, but also has a very high value for academic research.

The early image contour extraction method is similar as the extraction of keywords of a section of text, adds some properties labels to images, and the retrieval the properties labels. However, this method has some disadvantages, such as the labels can't express the information fully, completely. And the labels often have a certain degree of subjectivity. Currently, the methods used frequently are to extraction texture, color, shape and other characteristics of the images, and then we use the combination of the above mentioned features to complete the description of the image.

Technology of contour extraction has made a great improvement since 1990s.Mainly includes: First, OBIC image system led by IBM. This dynamic image retrieval system contains three subsystems, including: image storage, computer and inquiry by character [1]. Second, the photo book system that developed by MIT. This system finds a better way to resolve the problem of realtime computational overhead by using the three characters of grain, shape and face recognition when it runs [2]. Third, Netra system that led by University of California. It implements Gabor filter and neural network technology so that it can search image by region [3]. Forth, Virage system that developed by Virage. The features of the system are to allow users to adjust the weighting to improve the efficiency of searching. What Virage used in the system is the Virage engine developed by themselves. Fifth, Mars system that developed by university of Illinois. It mainly focuses on building a strong self-resilience searching mechanism [4].

Extracting the outline of the image is a very important part of intelligent vision system, the principle of traditional methods is mainly to extract the edge of the image, and then repair the image according to the relevant outline in time and exclude the redundancy. Perez uses JetStream's prior knowledge method to connect the edge section, and find the closed circles in the end, this method has some advantages such as the anti-noise performance is very good, but it is not good for images with sharp [5]. J Yang proposes a contour extraction method based on directional morphology, the advantage of this method is that it has more complete and rigorous theoretical foundation and can be adopted by computer easily. But it is easily to get into infinite loop in the discontinuous edge portion [6]. Yao QM proposes some improvements based on J Yang, and improves the anti-noise performance of the whole system [7]. S.Osher and J.A.Sethian propose the method of level set, reference the content of level set, and this method can deal with the Geometric topology change process of

closed moving interface, it has the feature that unrelated with stability and topology. Chan proposed a level set method based on Munford-shah optimal segmentation model, it can deal with the condition that the edge of the images is fuzzy or discrete [8]. In other areas, Malsburg and Vonden designed a series of neurons encoding mechanism on the relevant principles of neural dynamics to describe the synchronous information about contour, and this method makes a great contribution to subsequent work [9-10].

In recent years, multicore learning model as a new and flexible learning mode based on kernel gradually got all the attention, it thanks to the study about SVM theory at the same time, multicore learning instead of the mononuclear learning begins to penetrate many areas of machine learning. Especially when the samples are large-scale, heterogeneous information or irregular cube, multicore learning is more superior [11-12]. According to the capture of contour extraction, multicore learning has large value in the area for research [13].

Support Vector Machine (SVM) is one of the basic tools of machine learning. It can be widely used in the range from the visual bioinformatics to natural language processing. Also it can be used for classification, regression, etc. Support Vector Machine successfully applied in these areas depends on the kernel function and feature space which is needed to pre-selected manually. In fact, to select the kernel parameters and the feature space is very difficult. Through the training data set, Multiple Kernel Learning (MKL) can used to learn the kernel function to solve the above problem. Significantly, MKL focused on how to make this kernel function as a linear combination of given basic kernel function to learn [14].

During the analysis, we found that the premise of image contour extraction is contour recognition and detection, and contour detection is closely related to the problem: image segmentation, shape recognition, object recognition [15]. In this section it mainly included two parts, the first is about the feature of the image and the second is about the contour detector. And in the first part it is divided into three steps. The first step is the Gradient of image. When dealing the gradient of image, this paper used the width of the Gaussian kernel to calculate the gradient. And the metric values contain some information which is related to the image edge discontinuity. In the analysis it can find that the main feature of the contour detection. In the second step, it is about the structure control. It mainly used the filters to finish the inhibit areas of the texture. The detail process of the image contour extraction is as the following. So in this research, we come out with a learning algorithm to contour detection based on supporting vector machine. Many kernels are utilized to build a learning frame classifier that supports vector machine. These kernels not only contain the gradient, direction, suppression condition, brightness of the image, but also contain the gradient of image color and the features of compass operator. First of all, it will standardize all the probability of trees through learning the classifier. Second, it improves the detection

result through refining the operators. At last, the new proposed algorithm will be assessed based on the primary algorithm of Berkeley segmentation data set. The experiment method of this paper is better than other methods (such as GBP, BEL, etc.) whether it is in collection volume, the size of the data and the accuracy of the image after the image contour extraction. The result proves that it is a more efficient way to utilize multiple visual kernels and support vector classifier to do the contour detection [16].

II. PROPOSED SCHEME

To overcome the limitations of the previous methods for contour extraction, we in this paper propose a learning based method to attack this problem. The method is composed of two parts: (1) middle level image feature extraction; (2) multiple kernel learning classifiers for contour classification. The graphical illustration of the framework of the proposed method is shown in figure 1.
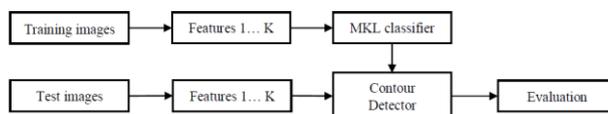

Figure 1.   The graphical illustration of the proposed method

As we all know, extracting the outline of the image is a very important part of intelligent vision system, the principle of traditional methods is mainly to extract the edge of the image, and then repair the image according to the relevant outline in time and exclude the redundancy.

Currently, for large-scale, heterogeneous digital image, the efficiency of many traditional image contour extraction method is low, and the result is often bad. For example, the method based on gradient is suitable for straight contour, and the method of prior knowledge drops into the local extreme value easily. According to this, the paper presents an image contour extraction method based on multiple kernels learning (MKL). The method uses multiple kernels to construct a framework for learning classifier, and then it uses the accumulation of learning classifier and regulates the probability of the output, then it can improve the test results by using the operator. The contour detection problem can be casted to a classification through associating the contour with the class label. That is, contour is a class while non-contour is another class.

A. Image Feature Extraction

(1) *Gradient of image*. Each image I use the width σ of the Gaussian kernel to calculate the gradient. The metric values of $|\nabla I|$ contains information related to image edge discontinuity, mainly including the strength, direction, or point of view. Gradient magnitude and direction is the main feature of contour detection as shown in Figure 2 (b) and (c).

(2) *Structure control*. Use the manageable filters to control inhibit areas of the texture, main show is:

$$t(x,y) = \{V_0 * |\nabla I|\}(x,y) + re\{e^{2i\theta_\nabla(x,y)}[(v_2 * |\nabla I|)(x,y)]\}$$

$$V_0(\rho,\Phi) = \frac{\rho^2}{2}, v_2(\rho,\Phi) = \frac{\rho^2}{2}e^{2i\Phi} \qquad (1)$$

In the equation, ρ and Φ are control parameters. It is shown in Figure 2 (d).

(3) *Brightness and Color Gradient*. Generally, utilizing brightness, color, texture and segmentation area for contour detection mainly use PB method and GPB method. In order to improve the efficiency, suppose there is a round disc with a radius r, when take pixels (x, y), diameter at angle of θ the disk is divided into two parts, using the histogram represents its brightness and color in the space BIELAB.

To calculate the distance x^2 of the two parts half a plate of histogram and oriented gradient $G(x,y,\theta,r)$ so that accomplish encoding of brightness and color gradient function, as shown in Figure 2 (e) and (f) [17-18].
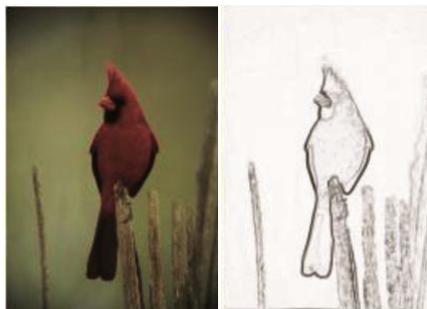

(a) Input (b) magnitude and gradient
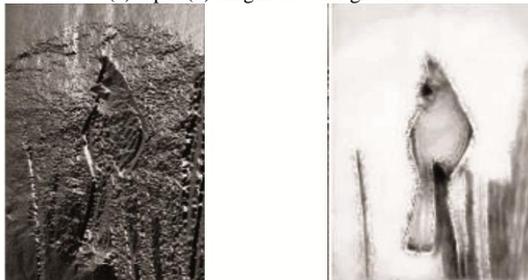
(c) Direction of gradient (d) inhibition term

(e) Brightness gradient (f) color gradient
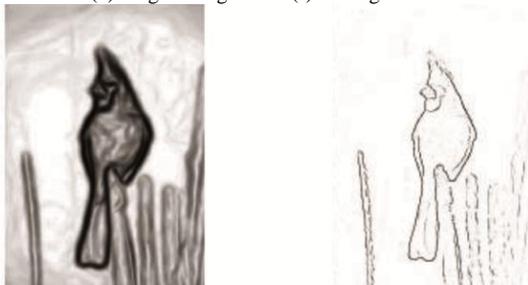
(g) Compass operator (h) the detected contour by our algorithm

Figure 2. Features of image

Compass operator determines the diameter direction of a separable disc on its each pixel (x, y). The distance between the two color logo computation equation shows below:

$$d_{ij} = 1 - \exp(-E_{ij}/\gamma) \qquad (2)$$

where E_{ij} indicates the European space between color i and color j, γ is fixed. The minimum value of the ball distance between color i and color j is:

$$\sum_{i\in S_1}\sum_{j\in S_2} d_{ij}f_{ij} \qquad (3)$$

where f_{ij} indicates the flow between color i and color j obey to all the constraints from S_1 to S_2. The result can be shows as function: $f(\theta)(0° \le \theta \le 180°)$.

B. Contour Detector

We normalize the Eigen values of each image within the range of 0 and 1, and form a feature vector by using these vectors. Namely, there is a six-dimensional feature vector in a pixel of the training image, and it makes up a Gaussian gradient (MG), Gaussian gradient direction (DG), the inhibition Time (IT), brightness gradient (BG), color gradient (CG) and the compass (CO) operation according to the degree of importance.

We cultivate a detector framework within the MKL which uses for contour detection. Multi-kernel algorithm has been shown to effectively and efficiently handle a large number of data points.

III. IMAGE CONTOUR EXTRACTION

A. The Problem Statement

Considering a set of labeled samples $(x_1, y_1),(x_2, y_2)$, $(x_1, y_1) \in X \times Y$, where the input space $X \subseteq R^n$ and the output space $Y = \{-1,+1\}$ for classification problem. Kernel methods map the input space to the feature space using the feature mapping φ:

$$\varphi: X \to F, x \mapsto \varphi(x) \qquad (4)$$

where $F = \{\varphi(x) \mid x \in X\} \subseteq R^n$. Then we use the data $(\varphi(x_1), y_1),(\varphi(x_2), y_2),\cdots,(\varphi(x_l), y_l) \in F \times Y$ instead.

Let $k: X \times X \to R$ be a continuous and symmetric function. There must exist a feature space F and a mapping $\varphi: X \to F$ satisfying:

$$k(x, z) = \varphi(x) \times \varphi(z)$$

Usually, different kernels are adopted for different tasks. The most frequently used kernel function is linear kernel, polynomial kernel, radial kernel, Sigmoid kernel.

B. Generalized Multiple Kernel Learning

Considering the general form of the decision function:

$$f(x) = w^t \varphi_d(x) + b \qquad (5)$$

where $k_d(x_i, x_j) = \phi_d^t(x_i)\phi_d^t(x_j)$ is the inner product over the feature space ϕ.

The learning problem of generalized multiple kernel learning is to determine the optimum value for w and b by fitting the training data $\{(x_i, y_i)\}$. Further, multiple kernel learning can used to estimate the kernel parameter d, which can be expressed as the following equation:

$$\frac{1}{2}w^t w + \sum_i l(y_i, f(x_i)) + r(d) \qquad (6)$$

where $d \geq 0$, r and the kernel can be any continuous and differentiable function with respect to d, l can be any cost function. Note that, the constraint $d \geq 0$ can be generalized to constraints of positive value.

TABLE I.   THE PROCEDURE OF MKL ALGORITHM

	MKL algorithm
1	$n \leftarrow 0$
2	Initialize d^0 randomly
3	Repeat
4	$K \leftarrow k(d^n)$
5	Select K, kernel, and α^* to solve single kernel problem
6	$d_k^{n+1} \leftarrow d_k^n - s^n(\frac{\partial r}{\partial d_k} - \frac{1}{2}\alpha^{*t}\frac{\partial H}{\partial d_k}\alpha^*)$
7	Mapping d^{n+1} to Feasible collection
8	$n \leftarrow n+1$
9	Untilconvergence
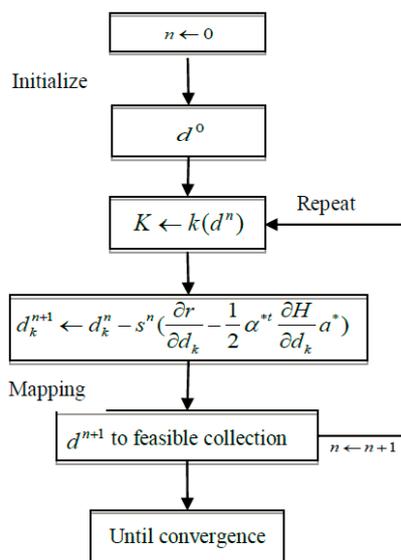
Figure 3.   The flow chart of MKLalgorithm

C. Optimization Procedure

For generalized multiple kernel learning, we use a standard approach to convert the original optimization problem to a nested two-step optimization problem. In the outer loop, the kernel learned while the parameters of decision function are fixed. In the inner loop, the kernel is fixed and the parameters of the decision function are determined. The original assumption is:

$$\min_d T(d) \text{ for } d \geq 0 \qquad (7)$$

where

$$T(d) = \min_{w,b} \frac{1}{2}w^t w + \sum_i l(y_i, f(x_i)) + r(d)$$

It can be proved that the gradient $\nabla_d T$ always exists, through the following equation,

$$W_c(d) = \max_\alpha 1^t \alpha - \frac{1}{2}\alpha^t Y K_d Y \alpha + r(d) \qquad (8)$$

where $1^t Y \alpha = 0, 0 \leq \alpha \leq C$, and

$$W_R(d) = \max 1^t Y \alpha - \frac{1}{2}\alpha^t K_d \alpha + r(d) - \varepsilon 1^t |\alpha| \qquad \text{where}$$

$1^t \alpha = 0$, $|\alpha| \leq C$; K_d is the kernel matrix; Y is a diagonal matrix of labels. Considering the duality, we have $T = r + P$ and $W = r + D$. For any given d, the following equation holds,

$$T(d) = W(d)$$

If $k, r, \nabla_d k, \nabla_d r$ is the function of d, such that W takes the optimal value, then we have the following equation:

$$\frac{\partial T}{\partial d_k} = \frac{\partial_r}{\partial d_k} - \frac{1}{2}\alpha^{*t}\frac{\partial H}{\partial d_k}\alpha^* \qquad (9)$$

Generalized multiple kernel learning can be used for classification when setting $H = YKY$; and can be used for regression when setting $H = K$. The learning procedure of generalized multiple kernel learning is reported in Table 1. And the flow chart of the algorithm are illustrated in Figure 3.

IV.   EXPERIMENTAL RESULTS

Selecting the data sets with 500 pictures included, the pictures used in this paper are all from Corel image library and the internet data. There are many types of the pictures, such avatars, natural landscape, buildings, plants, flowers, natural animals and so on. The size of these pictures is 481x321, and it is the result of human's fragmenting. By using the method to contour detection, we can have a representative result.

In the first experiment, in order to make a comparison, we use other 300 pictures to train, and the other is used for a test. Contour pixels of the ground truth are used as the positive examples of training sets, we also described them by using six - dimensional feature vector, the other are used as the counter examples. All the experiments are operated in the machine with 3.10 GHz CPU and 16 GB memory. We can refer to the content mentioned in Section 2.1 above for the processing process. Describing the image by using image feature, repeating the test many times, letting the mean repeating test results as the feature value of the images, and we can calculate. In the experiment we used a combination of different functions to assess the results of MKL classification contour detection. At the same time, we can use the equation:

$$\frac{2*precision + recall}{precision + recall} \qquad (10)$$

During the experiment it used the result of the above equation as the evaluation criterion. The experiment results can be shown in Figure 4. From the experiment result we can see with the increasing of F value, the precision will be higher. But the change is not obvious. The reasons accounting for the outperformance of the proposed MKL method over other compared methods are twofold. First, the Kernel method combines the Kernel functions by a certain principles, from which it can get higher mapping performance. So it can promote to get high precise classify results. Second, MKL exploits the ability of the nonlinear feature mapping through learning the implicit feature space. By means of learning nonlinear feature mapping, the classifier could adapt to data distribution well. The adaptability of MKL comes from the flexibility and the adaptability of the parameters of kernels of MKL.

In the second experiment, because of the selection of divided regions and contour are based on the size, we can first use a training sets to determine the size of the optimal data base (ODB), and restore all the test images. When the optimal image scale (OIS) of each image in full recall average precision (AP), we can assess the performance. The experiment parameters are four typical sets: MG+DG+IT+CG+BG+CO, MG+DG+IT+CG+BG, MG+DG+IT+CG and MG+DG+IT. In the experiment it used the average precision as the assessment standard. Table 2 shows that the test contour results of F, we use a combination of different functions to make classified metric in MKL. All these experimental results show that the classification using a combination of all functions which bases on MKL performance the best. The reasons accounting for the outperformance of the proposed MKL method over other compared methods are twofold. First, MKL exploits the ability of the nonlinear feature mapping by learning an implicit feature space, by which the classifier could adapt to data distribution well. The adaptability essentially comes from the flexibility of the parameters of kernels of MKL. Second, in the context of combining several feature extraction methods, MKL is able to exploit much larger feature space, which provides richer contour detection information.
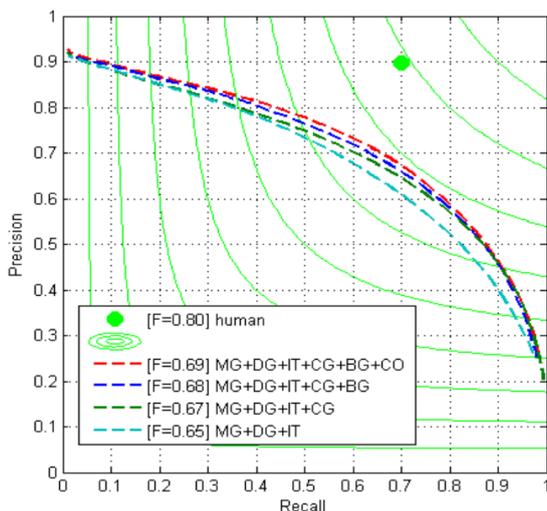

Figure 4. Different function combination of precision-recall curve

TABLE II. DIFFERENT FUNCTION OF F-VALUE COMBINATION

Dataset BSDS500			
	Best dataset	Best image scale	Average precision
Human	0.80	0.80	—
MG+DG+IT+CG+BG+CO	0.69	0.71	0.72
MG+DG+IT+CG+BG	0.68	0.70	0.71
MG+DG+IT+CG	0.67	0.69	0.70
MG+DG+IT	0.65	0.67	0.68
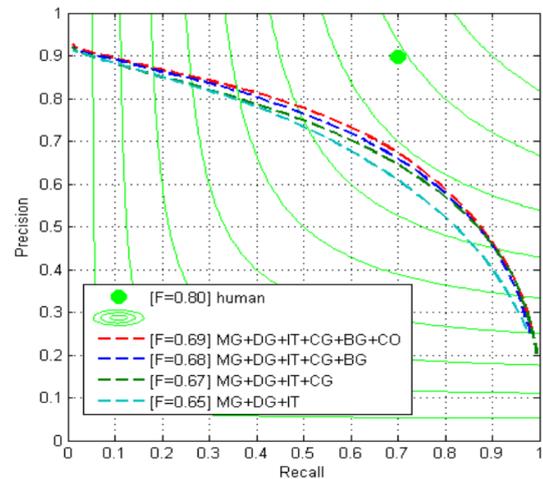
Figure 5. Contour detector accuracy held curve

TABLE III. F-VALUE OF CONTOUR DETECTOR

Dataset BSDS500			
	Best dataset	Best image scale	Average precision
human	0.80	0.80	—
Gpb	0.71	0.74	0.65
MKL	0.69	0.71	0.72
BEL	0.66	0.67	0.68
Canny	0.60	0.63	0.58
Compass	0.49	0.53	0.36

In the third experiment, it shows the recall ratio curve and F-test under the condition of different threshold and precision. Then though the experiment we can see which threshold will have the highest precision. The experiment parameters are GPB, MKL, BEL, Canny and Compass. In the experiment it used the average precision, best dataset and best image scale as the assessment standard. In Figure 5 and Table 3 they show the experiment results. From the result we can see that GPM method performed well in terms of accuracy, but it is far slower than the suggested MKL algorithm. On average, the GPB algorithm need about 150 seconds to detect the contour in an image, but the mentioned MKL algorithm takes only 9 seconds [19]. The primary reasons accounting for the outperformance of the proposed MKL method over other compared methods are threefold. First, MKL exploits the ability of the nonlinear feature mapping through learning the implicit feature space. By means of learning nonlinear feature mapping, the classifier could adapt to data distribution well. The adaptability of MKL comes from the flexibility and the adaptability of the parameters of kernels of MKL. Second, the combinations of several feature extraction methods capture rich information on the contour from the images, which will significantly facilitate the contour detection. Third, the cooperation of

feature extraction methods and MKL excites the potential of SMKL algorithm.

(a) Hand image

(b) Hand image

(c) edge map(faulty)
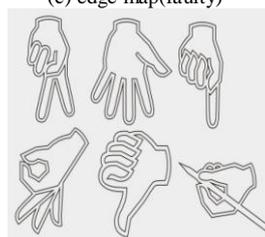
(d) edge map (faulty)

Figure 6.   Experimental results of manual image

In the fourth experiment, it was used to test the recall ratio curve and F-test under the condition of different threshold and precision. In the experiment it used the

different hand image and edge map to test the F-value as the assessment standard [20-21]. The experiment results can be seen in figure 6. From the test result we can see that from a picture we can get the different edge maps by using the Contour detector. From the result we can see that in the different function of F-value combination we can get the different average precision. When the best dataset is 0.69 and the best image scale is 0.71, it has high average precision. From the experiment result we also can see that the method in this paper is better than other methods (such as GBP, BEL, etc.) whether it is in collection volume, the size of the data and the accuracy of the image after the image contour extraction. The result proves that it is a more efficient way to utilize multiple visual kernels and support vector classifier to do the contour detection.

V.   CONCLUSIONS

Using MKL method, we can extract the gradient of the image feature, control the structure of the image and describe the brightness of the image and the color gradient by using histogram. The algorithm uses a compass operator and constructs the contour detector finally. The detector can make every pixel be described by the feature vector of the six dimensions(Gaussian gradient (MG), Gaussian gradient direction (DG), the inhibition Time (IT), Brightness gradient (BG), Color gradients (CG) and Compass operation (CO)), and in the end, we can obtain the information of contour.

Multiple kernels learning method has some advantages when compared with single kernel learning methods and other intelligent methods especially in solving complex problems, MKL method can provide some help for image retrieval. However, MKL algorithm itself also has some disadvantages, such as how to deal with the relationship among a good number of kernels and there is still a large room for improvement on how to determine the coefficient effectively when using MKL methods. Additionally, there is still not a good way for the method of synthesis kernel when samples are not evenly distributed and it is still not a study of multiple dimensional in true sense. All these problems are needed to be listed in our further study.

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