Image Classification Using No-balance Binary Tree Relevance Vector Machine

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Abstract—**Nowadays, Image classification method has been widely researched in the world. In this paper, we prepare four building categories for database. Firstly we use the Gabor filter for image processing to extract the image features, and then divide the images to different subregions for histogram-based Gabor features. At last, for image classification, Support Vector Machine (SVM) and Relevance Vector Machine (RVM) are known to outperform classical supervised classification algorithms. SVM has excellent performance to solve binary classification problems. RVM could be more sparsity than SVM. A new method based on relevance vector machine— No-balance Binary Tree Relevance Vector Machine (NBBTRVM) is proposed to define a class in this classification task. NBBTRVM could do a good performance according to our experiment results.**

Keywords- Image Classification; Gabor filter; Histogram; Support Vector Machine (SVM); Direct Acyclic Graph Support Vector Machine (DAGSVM); No-balance Binary Tree Relevance Vector Machine (NBBTRVM).

I. INTRODUCTION

In the last few years, there have been significant developments in the theoretical understanding between Support Vector Machine (SVM) and Relevance Vector Machine (RVM); and also image classification has widely applications in our every day of life. Image database could be available from our camera, video and even internet. For this task, we prepare four building categories such as insidecity, street, suburb and tallbuilding.

After preparing the database, the main body of this paper is organized in three parts. In the first part we introduce Gabor filter. Because of the multi-convolution property, the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of harmonic function and the Fourier transform of Gaussian function[1] [2]. Due to the complexity of multi-scale Gabor filter, we specially set different numbers of frequency level. And then our work is denoted to finding suitable representation for images. We should fix the diversified subregion after applying Gabor filter because of object position nondeterminacy. In so doing, we pave the way for next step, which is to calculate the orientation histogram based on Gabor feature extraction. Here, we want to point out even Gabor features are efficient for the following analysis; the simple clustering algorithm does not make the multi-class features compact. To avoid this defect, histogram-based Gabor features will be used which could obtain more related information over neiboring pixels.

The last part of this paper deals with classification problems. The aim of classification using SVM is to construct a hydroplane in a high dimensional feature space as the decision surface in such a way that the margin of separation between positive and negative examples is maximized. In these years, it is reported that RVM is a good alternative to the popular SVM [3]. Polynomial inner-product kernel exploits information about the inner products between data items. Then, give the details of three approaches for multi-class problems. Finally, Conclusions will be presented, the SVM has a high generalization ability to solve binary classification problem, but its extension to multi-class problems is still an ongoing research issue compared to DAGSVM, which is actually constructed by a certain amount of binary SVM, to deal with the multi-classification. Further more; NBBTRVM which we proposed has improved classification accuracy to DAGSVM and works fairly well in efficiency. Experiment results are presented in this paper as well.

II. GABOR FILTER

In the last three decades, the multi-orientation histogram for feature extraction is widely reported [4] [5]. Gabor filter is given by

$$\psi_k(z)=\frac{k^2}{\sigma}\exp\left(\frac{-k^2z^2}{2\sigma^2}\right).\left(\exp(ikz)-\exp\left(-\frac{\sigma^2}{2}\right)\right) \tag{1}$$

In this equation, $z=(x,y)^T$, $k=k_v\exp(i\phi)$, $\phi=\mu\cdot\frac{\pi}{8}$, $k_v=\frac{k_{\max}}{f^v}$, $f=\sqrt{2}$ and $\sigma=\pi$ .We set $\mu=\{0,1,2,3,4,5,6,7\}$ for 8 different orientations and $v=\{0,1,2\}$ for 3 frequency levels. The sizes of Gabor filters are set to 5×5 , 10×10 and 15×15 respectively. Figure 1 shows the results of 8 different orientations for one image using Gabor filter.

More importantly, the subregion sizes from the output of Gabor filter should be considered [6]. Eight different subregion sizes are fixed before in the case of no predetermined best subregion. Next, for each subregion

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we develop the histogram of 8 orientations. As we introduced before, we prepared 3 scales and 97 subregion sizes. So the length of reshaped vector for one image should be 2,328.

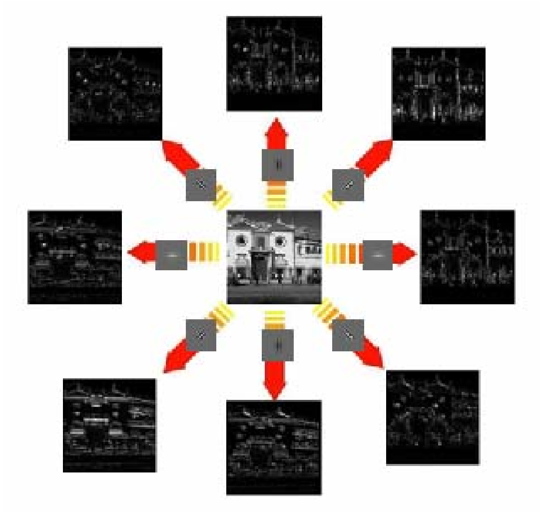

Figure 1: Images of 8 different orientations using Gabor filter

III. MUTI-CLASSIFICATION USING SVM

The SVM model is the maximal margin classifier, which works only for linearly separable data in the feature space. The original optimal hyperplane algorithm proposed by Vladimir Vapnik in 1963 was a linear classifier. Considering the non-linear case might exist, the linear transform $\phi(\mathbf{x})$ could be used.

$$f(\mathbf{x},\alpha,b)=\sum_{i=1}^{\eta} y_i\alpha_i\phi(\mathbf{x}_i)^T\phi(\mathbf{x})+b \qquad (2)$$

However, in 1992, Bernhard Boser, Isabelle Guyon and Vapnik suggested a way to create non-linear classifiers by applying the kernel trick to maximum-margin hyperplanes [7] [8]. To avoid samples mapping into high dimensional space by $\phi(\mathbf{x})$ .we define the kernel function as follows,

$$\mathbf{k}(\mathbf{x},\mathbf{z})=\langle\phi(\mathbf{x})\cdot\phi(z)\rangle \qquad (3)$$

Recently, it is reported that the normalized Polynomial kernel does good performance. In this paper, we select this kernel as the kernel function. It is defined as,

$$\mathbf{k}(\mathbf{x},\mathbf{z})=\frac{\phi(\mathbf{x})^T\phi(\mathbf{z})}{\|\phi(\mathbf{x})\|\cdot\|\phi(\mathbf{z})\|}=\frac{(\mathbf{x}^T\cdot\mathbf{z}+c)^d}{\sqrt{(\mathbf{x}^T\cdot\mathbf{x}+c)^d(\mathbf{z}^T\cdot\mathbf{z}+c)^d}} \qquad (4)$$

Because we prepare four building categories, the classification is a multi-class issue. Two approaches are widely talked which are One-Against-All method and One-Against-One method. Because we want to compare the veracity between the binary classification and the multi-classification, One-Against-All method and DAGSVM method will be used for the following experiments, we should construct k SVM models for One-Against-All method. Figure 2 shows One-Against-All method phase. The final output is the category which corresponds with the highest output value.

$$\textit{the class of } x=\textit{argmax}_{\boldsymbol{i}=1,\ldots\boldsymbol{k}}\left(\langle\boldsymbol{\phi}(\mathbf{x})\cdot\mathbf{w}^{\boldsymbol{i}}\rangle+\boldsymbol{b}^{\boldsymbol{i}}\right) \qquad (5)$$

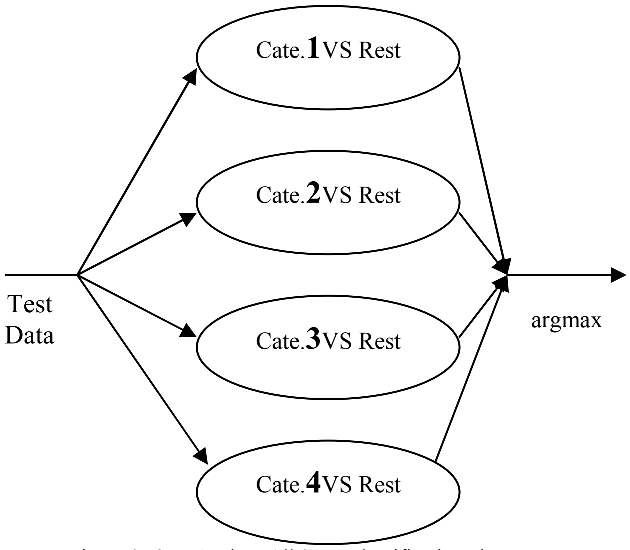

Figure 2: One-Against-All SVM classification phase

A Directed Acyclic Graph (DAG) is a graph whose edges have an orientation and no cycles. In DAGSVM, each Binary DAG has 2 arcs leaving it except the root graph which has nothing pointing it. Figure 3 shows the sketch map of DAGSVM decision for testing based on the four classes:

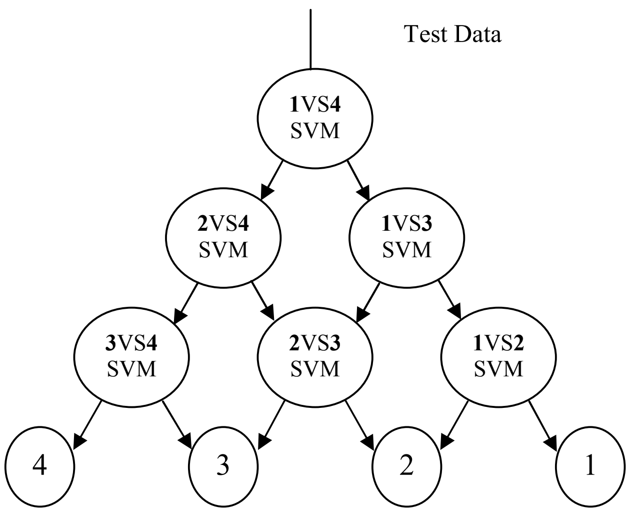

Figure 3: DAGSVM classification phase

In the training phase of DAGSVM, $k(k-1)/2$ binary SVMs are running respectively. Here, we set k equal to 4. In the testing phase, the classification is specifically starting at the root node. For one of the nodes which is a binary SVM and we assume it made by category

i and category j, provided $i < j$. This node can decide the input data either not category i or not category j, and then give a new direction to the lower layer. Therefore a decision path is passed before a leaf node is reached. For a k-class problem, the class could be defined via $k-1$ nodes. The training phase of this method is the same as One-Against-All method but its testing time is less than One-Against-All method .

IV. NBBTRVM

RVM, pioneered by Tipping in 2001 is a Bayesian sparse kernel technique for regression and classification. It is similar to SVM in many respects but prediction is probabilistic due to its advantage to yield a decision function sparser than SVM [9]. RVM tries to catch a hyperplane as a weighted combination.

The prediction form of RVM can be put as,

$$f(\mathbf{x}) = \sum_{i=1}^{\eta} w_i \mathbf{K}\langle \mathbf{x} \cdot \mathbf{x}_i \rangle + w_0, \tag{6}$$

Where $\mathbf{K}\langle \mathbf{x} \cdot \mathbf{x}_i \rangle$ is a kernel function and w_i is model weights. In our paper, because we would like to compare the classification accuracy based on different classifiers, so we keep normalized Polynomial kernel same as prior experiment. RVM performs classification by predicting the posterior probability given $f(\mathbf{x})$, that is,

$$P(y / f(\mathrm{x})) = \frac{1}{1+e^{-f(\mathrm{x})}}, \tag{7}$$

A sample $\mathbf{X}$ is classified to the class $y \in \{-1,+1\}$, which maximized the conditional probability $P(y / f(\mathrm{x}))$. In this paper, we proposed non-balanced binary tree. Our multi-class classification issue is a combination with $(k-1)$ binary tree RVMs. According to our experiment, we set $k=4$ as well. The construction order of binary tree influences the classification accuracy heavily, so we proposed the flowing steps to avoid it.

For a training set of data $(x_i)_{i=1}^{\eta}$ where $x_i \in \Re^n$ are the input feature vectors,

- Compute the separability measure of each class $\delta_i = \frac{\|c_j - c_i\|}{\delta_j + \delta_i}$, where c_i, c_j is the cluster center of class i, j individually, δ_j is the cluster variance of class j.
- Select the minimum separability measure of two classes among them, the two classes can be considered as a new big class X_1. The number of category should minus 1.
- Repeat first step until only two classes left. So these two classes contribute to a binary RVM.
- Get the multi-class classifier by constructing modes from the root node of binary tree in sequence. We present this phase in Figure 4.

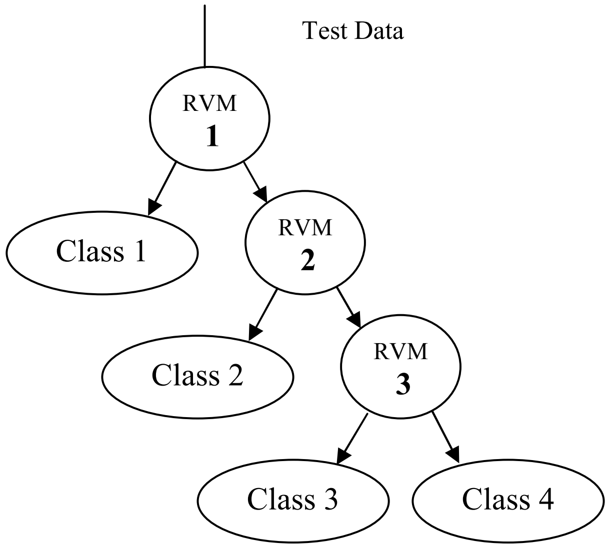

Figure 4: NBBTRVM classification phase

V. EXPERIMENTS

In this experiment, we prepared 4 gray-scale building categories including insidecity, street, suburb and tallbuilding. The examples of image database are shown in Figure 5. For each category the image database totally 200 images are divided into two sets averagely as training and testing images.

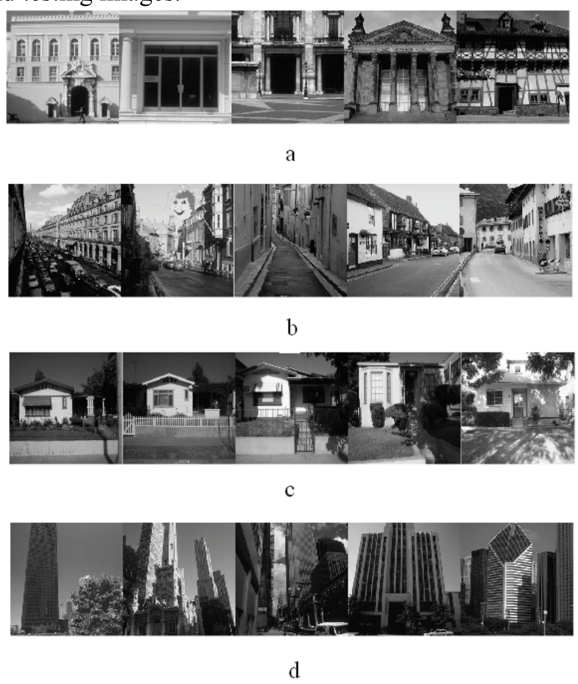

Figure 5: Examples of building database
(a. insidecity, b. street, c. suburb, d. tallbuilding)

As we proposed before, multi-resolution orientation histogram of 2,328 dimensions for each image is prepared in advance. We use three types of classifiers, which are respectively One-Against-All SVM, DAGSVM and NBBTRVM. Classification accuracies are shown in Table 1.

In the case of One-Against-All SVM applied, the best average accuracy for four building categories is 79.00% when kernel parameter c=5, d=10. The best average accuracy for DAGSVM is improved to 85.25% when c=10, d=5.

However, we could easily observe that NBBTRVM which we proposed performs much better than OAASVM and DAGSVM under various kernel parameter values. The best average accuracy is 90.50% when c=5, d=10.

Table 2 shows the classification time under 3 methods. NBBTRVM's running time less than the other two methods.

Table 2: Running Time when c=5, d=10

	Accuracy	Time(s)
OAASVM	79.00%	35.27
DAGSVM	84.25%	33.68
NBBTRVM	90.50%	24.92

VI. CONCLUSION

Various subregion sizes are prepared for computing the orientation histogram since we don't know the most appropriate size in advance.

The accuracy heavily depends on the parameters of kernel, so we perform many experiments among different parameters.

In this paper, we compared the classification ability and efficiency of One-Against-All SVM, DAGSVM and also NBBTRVM respectively based on multi-resolution orientation histograms and obtained the conclusion, the NBBTRVM could perform much better than both One-Against-All SVM and DAGSVM, and by the way, DAGSVM could improve the final accuracy compared One-Against-All SVM, that proved SVM goes well specially in binary classification.

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Table 1: Classification accuracy using One-Against-All SVM (OAASVM), DAGSVM, and NBBTRVM with different kernel parameter values

Kernel Parameter		c		
		1	5	10
d	1	OAASVM 71.25%	OAASVM 64.50%	OAASVM 62.75%
		DAGSVM 76.00%	DAGSVM 74.75%	DAGSVM 75.00%
		NBBTRVM 76.25%	**NBBTRVM** 78.00%	**NBBTRVM** 80.75%
	5	OAASVM 57.50%	OAASVM 65.50%	OAASVM 71.50%
		DAGSVM 75.50%	DAGSVM 80.75%	DAGSVM 85.25%
		NBBTRVM 85.50%	**NBBTRVM** 88.00%	**NBBTRVM** 87.25%
	10	OAASVM 64.25%	OAASVM 79.00%	OAASVM 73.50%
		DAGSVM 80.25%	DAGSVM 84.25%	DAGSVM 82.50%
		NBBTRVM 81.00%	**NBBTRVM** 90.50%	**NBBTRVM** 85.25%