STUDY ON IMAGE CLASSIFICATION BASED ON SVM AND THE FUSION OF MULTIPLE FEATURES

Dequan Zheng, Tiejun Zhao, Sheng Li and Yufeng Li
MOE-MS Key Laboratory of Natural Language Processing and Speech
Harbin Institute of Technology, Harbin 150001, P. R. China

Keywords: Image classification, Fusion, Multiple features, SVM.

Abstract: In this paper, an adaptive feature-weight adjusted image classification method is proposed, which is based on the SVM and the fusion of multiple features. Firstly, classifier was separately constructed for each image feature, then automatically learn the weight coefficient of each feature by training data set and the classifiers constructed. At last, a complexity classifier is created by combining the separate classifier and the corresponding weight coefficient. The experiment result showed that our scheme improved the performance of image classification and had adaptive ability comparing with general approach. Moreover, the scheme has certain robustness because of avoiding the impact brought by various dimension of each feature.

1 INTRODUCTION

With the development of information and multimedia technology, image has become an important component of WWW content. It is necessary to develop intelligent system to retrieve and categorize images based on their visual contents. In computer vision domain, image retrieval and categorization have become researching hot pot for recent several years (Vailaya, Figueiredo, etc. 2001).

Different from traditional image retrieval issue, image categorization can be well pre-defined in specific domain and specific categories, such as sports image categorization in the Olympic Games. Specifically, image categorization is to give label information for each image. For example, if we classify images of the Olympic Games, the system can automatically label each image with sports categories information, such as swimming, volleyball, lifting, table tennis, gymnastics, etc. For image retrieval, image categorization not only can meet user's semantic retrieval demand by category-specific search, but also can reduce retrieval time by weeding out irrelevant images in the process of retrieval.

At present, it is the main method of image categorization that extracting visual features by image analysis technology firstly, then building classification model by machine learning algorithm, at last predicting semantic label information by classification model. Youna integrated both texture and four color features to express each image and implemented sports image categorization by Bayesian classifier (Youna, Eenjun, etc. 2004). Chang and Goh adopted SVM and global visual feature to implement image categorization (Chang, Goh, etc. 2003). As a result of image data's characteristic, image visual feature's extraction and expression are important barriers, which restrict the performance of image categorization. Generally speaking, one kind of visual feature isn't able to express image contents well. Therefore, researchers usually extract several kinds of visual feature to express image contents. But each feature has different importance in an image. When we adopt several kinds of visual feature to express image content, there is an obvious shortcoming if we simply combine multiple visual features into a feature vector. It is not nimble to adjust influence coefficient of each feature to image classification, this shortcoming seriously influences the effect of image classification.

In this paper, we proposed an adaptive feature-weight adjusted image categorization algorithm based on the SVM and the fusion of multiple features. The algorithm is able to automatically learn feature-weight coefficient of each feature, which solves the shortcoming of combining multiple visual features into a feature vector and improves the performance of image categorization.

The rest of this paper is organized as follows:

Zheng D., Zhao T., Li S. and Li Y. (2009).
STUDY ON IMAGE CLASSIFICATION BASED ON SVM AND THE FUSION OF MULTIPLE FEATURES.
In *Proceedings of the 11th International Conference on Enterprise Information Systems - Artificial Intelligence and Decision Support Systems*, pages 81-85
DOI: 10.5220/0001864200810085

Section 2 gives a brief introduction of SVM and multi-class classifier. Section 3 presents our image categorization algorithm based on the SVM and the fusion of multiple features. Section 4 shows the experimental result of our algorithm. Finally this paper concludes in Section 5.

2 SVM AND MULTI-CLASS CLASSIFIER

SVM is a very effective binary classification algorithm (Burges, 1998), it aims at separating two classes of training samples in feature space by an optimal hyper-plane, where the maximum geometric margin gains.

Given a binary classification problem, where x_i is a n-dimension vector and y_i is the label of the class that the vector belongs to:

$$\{(x_i, y_i)\}\ s.t.\ i = 1,2,3\cdots N, y_i = \{+1,-1\} \tag{1}$$

The searching for optimal separating hyperplane $w^T x + b = 0$ is to maximize the geometric margin $\frac{2}{\|w\|}$ in vector space, subject to:

$$y_i(w^T x + b) \ge 1 \tag{2}$$

The solution can be found through a Wolfe dual problem with Lagrangian multiplied α_i:

$$Q(a) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j) \tag{3}$$

Subject to $\alpha_i \ge 0$ and $\sum_{i=1}^{N}\alpha_i y_i = 0$.

In the dual format, the data points only appear in the inner product. To get a potentially better representation of the data, the data points are mapped into the Hilbert inner product space through a replacement:

$$x_i \cdot x_j \to \phi(x_i)\cdot\phi(x_j) = K(x_i, x_j) \tag{4}$$

Where $k(\cdot)$ is a kernel function. Then we get the kernel version of the Wolfe dual problem:

$$Q(a) = \sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j K(x_i \cdot x_j) \tag{5}$$

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

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{l}\alpha_i y_i K(x_i, x) + b^*) \tag{6}$$

The output of the SVM classifier is the binary classification result. The further the data point is away from the hyperplane, the more confident the classifying result on this data point is.

However, as a binary classification algorithm, SVM would meet problems when comes to multiple-class image classification problem. Many methods have been proposed to combine binary classifiers to form a multi-class classifier. Traditionally, two replacements are adopted when it comes to multiple-class situation.

(1) One-against-All: For each category, training an intra-class classifier which indicates the sample’s confidence level of its category membership. Then normalizing their outputs. For each test sample, these classifiers of all categories are used to gain outputs, in which the category with the highest output is selected as the classification result.

(2) One-against-One: For each category, training n-1 inter-class classifiers between current category and other categories (supposing there are n categories). Then normalizing their outputs. For each test sample, the confidence level of each category is the majority voting result of these classifiers. The category with the highest sum of outputs is selected as the classification result. It combines the output of all classifiers to form an integrated prediction.

Hsu and Lin proved that the One-against-One method had better performance than the one-against-all method by experiment and theoretical analysis (Hsu and Lin, 2002). In this paper, we adopt the One-against-One method when we construct SVM multi-class classifier based on individual visual feature.

3 IMAGE CATEGORIZATION METHOD

The core idea of the image categorization algorithm based on SVM and the fusion of multiple features is: in the training stage, we firstly construct SVM multi-class classifier based on individual visual feature (such as color feature, texture feature and shape feature) by the One-against-One method (Wu, Lin, etc. 2004), then the algorithm automatically learns the weight coefficient of each feature by feature-weight learning module, which predicts the category information of every image in training dataset through the constructed classifiers; in the predicting stage, we firstly gain the confidence level value of the image belonging to each category by every SVM multi-class classifier based on individual visual feature, then we calculate the confidence level value of the image belonging to each category by combining each confidence level value gained and corresponding feature-weight coefficient, the category which gains the greatest confidence level value is the image's category according to the least error principle.

The image categorization algorithm proposed in this paper is composed of the model training algorithm, the learning algorithm of feature-weight and the predicting algorithm.

3.1 Model Training Algorithm

(1) Input:
training samples of image category $S_1, S_2, \ldots, S_n$.

(2) Training SVM multi-class classifier based on color feature SVM_{color} by One-against-One method.

(3) Training SVM multi-class classifier based on texture feature $SVM_{texture}$ by One-against-One method.

(4) Training SVM multi-class classifier based on shape feature SVM_{shape} by One-against-One method.

(5) Output:
$SVM_{color}, SVM_{texture}, SVM_{shape}$.

3.2 Learning Algorithm of Feature-Weight

(1) Input:
$SVM_{color}, SVM_{texture}, SVM_{shape}$, training samples of image category $S_1, S_2, \ldots, S_n$

(2) Initializing:
$weight\_color, weight\_texture, weight\_shape$ with zero.

(3) Predicting category information with $SVM_{color}, SVM_{texture}, SVM_{shape}$ for each image in training samples.

(4) If SVM_{color} gives correct category information, $weight\_color{+}{+}$; if $SVM_{texture}$ gives correct category information, $weight\_texture{+}{+}$; if SVM_{shape} gives correct category information, $weight\_shape{+}{+}$.

(5) Normalizing:
$weight\_color, weight\_texture, weight\_shape$

(6) Output:
$weight\_color, weight\_texture, weight\_shape$

3.3 Predicting Algorithm

(1) Input:
color-feature-vector, texture-feature-vector, shape-feature-vector.

(2) Gaining confidence level value of the image belonging to each category by color-feature-vector and SVM_{color}, $color\_p_1, color\_p_2, \cdots, color\_p_n$.

(3) Gaining confidence level value of the image belonging to each category by texture-feature-vector and $SVM_{texture}$, $texture\_p_1, texture\_p_2, \cdots, texture\_p_n$.

(4) Gaining confidence level value of the image belonging to each category by shape-feature-vector and SVM_{shape}, $shape\_p_1, shape\_p_2, \cdots, shape\_p_n$.

(5) Calculating the confidence level value of the image belonging to each category by combining each confidence level value gained and corresponding feature-weight coefficient. $p_1, p_2, \ldots, p_n$.

$$p_j = weight\_color \times color\_p_j + weight\_texture \times texture\_p_j + weight\_shape \times shape\_p_j$$

(6) $Label = \arg\max\{p_1, p_2, \cdots, p_n\}$.

(7) Output:
Image category label.

4 EXPERIMENT RESULT AND DISCUSSION

Our image database is consisted of 8 sports categories with each 100 images: soccer, basketball, tennis, volleyball, table tennis, swimming, weight lifting, gymnastics, shooting, and jiujitsu. Then, this database is divided into 2 sub-databases, one for training and the other for test. Both of them contain 8 categories with each 50 images.

Two experiments are conducted to verify the efficiency of our algorithm.

(1) General method: combining color feature, texture feature and shape feature into one feature vector, training one SVM multi-class classifier.

(2) Our scheme: firstly, constructing SVM multi-class classifier on each individual feature, secondly,

learning the weight coefficient of each feature by training dataset and the classifiers constructed, finally combining each SVM multi-class classifier based on individual feature and the corresponding weight coefficient into a complexity classifier.

Since our goal is to verify the efficiency of image categorization algorithm we proposed, the feature extraction method is simple and straightforward, where color histogram (Panchanathan, Park, etc. 2000), texture co-occurrence (Haralick, Shanmugam, etc. 1973) and shape invariant moment (Yao and Zhang, 2000) are extracted for each image.

In the experiment, we use binary classifier in LibSVM tool kits as core classifier to construct SVM multi-class classifier (Chang and Lin). Three criterions are considered: precision, Recall, F-score. Furthermore, in order to more clearly compare the two methods, we compute macro-precision, macro-recall, macro-F-score for each method.

Table 1: Results of general method.

Cat.	B	So	V	Tt
Precision	87.8%	93.5%	83.3%	100%
Recall	86%	86%	70%	88%
F-score	86.9%	89.6%	76.1%	93.6%
Cat.	Sw	Wl	G	Sh
Precision	95.7%	71.2%	81.3%	81.0%
Recall	90%	94%	78%	94%
F-score	92.8%	81.0%	79.6%	87.0%

Table 2: Results of our method.

Cat.	B	So	V	Tt
Precision	97.6%	93.3%	80.7%	100%
Recall	84%	84%	84%	86%
F-score	90.3%	88.4%	82.3%	92.5%
Cat.	Sw	Wl	G	Sh
Precision	90.3%	79.0%	80%	79.6%
Recall	94%	98%	80%	86%
F-score	92.1%	87.5%	80%	82.7%

Table 3: Comparison of the two methods.

Items	Macro-Precision	Macro-Recall	Macro-F-score
General method	86.73%	86%	86.2%
Our method	87.56%	87%	87.3%

As demonstrated in table 1 and table 2, our method improves the performance of image categorization comparing with general method. And this improvement is quantitatively demonstrated by their macro-precision, macro-recall and macro-F-score comparison in table 3. Furthermore, the method proposed in this paper has an obvious advantage of automatically learning each feature's feature-weight, so that it has certain adaptive capacity and adjusted ability, when it trains and predicts other categories of images.

5 CONCLUSIONS

In this paper, an image categorization algorithm is proposed to address the shorting of combining all the features into one feature vector. The algorithm firstly constructs SVM classifiers based on individual feature and automatically learns each feature's weight coefficient, then combines SVM classifiers and corresponding weight coefficient into a complexity classifier. As demonstrated in the experiments, our method improves the performance of image categorization.

ACKNOWLEDGEMENTS

This work is supported by the national natural science foundation of China (No. 60736044) and the National High-Tech Development 863 Program of China (No.2006AA010108).

REFERENCES

Vailaya, A., Figueiredo, M. A. T., Jain, A. K., Zhang, H. J., 2001. Image Classification for Content-Based Indexing. IEEE Transactions on Image Processing, Vol.10, 117-130.

Youna, J., Eenjun, H., Wonil, K., 2004. Sports Image Classification through Bayesian Classifier. Lecture Notes in Computer Science, Vol.3040, 546-555.

Chang, E., Goh, K., Sychay, G., Wu, G., 2003. CBSA: Content-Based Soft Annotation for Multimodal Image retrieval using Bayes Point Machines. IEEE Transactions on Circuits and Systems for Video Technology, Vol.13, 26-38.

Burges, J. C., 1998. A Tutorial on Support Vector Machines for Pattern Recognition. Data Mining and Knowledge Discovery, Vol.2, 121-167.

Hsu, C. W., Lin, C. J., 2002. A Comparison of Methods for Multi-class Support vector Machines [J]. IEEE Transactions on Neural Networks, Vol.13, 415-425.

Wu, T. F., Lin, C. J., Weng, R. C., 2004. Probability Estimates for Multi-class Classification by Pairwise Coupling. Journal of Machine Learning Research, Vol.5, 975-1005.

Panchanathan, S., Park, Y. C., Kim, K. S., Golshani, F.,

2000. The Role of Color in Content-Based Image Retrieval. International Conference on Image Processing, Vol.1, 517-520.

Haralick, R. M., Shanmugam, K., Dinstein, I., 1973. Texture Features for Image Classification. IEEE Transaction on System Man Cybern, Vol. 3, 610-621.

Yao, Y. R., Zhang, Y. J., 2000. Shape-based image retrieval using Wavelet and Moment. Journal of Image and Graphics, Vol. 5, 206-210.

Chang, C. C., Lin, C. J. LIBSVM: A Library for Support Vector Machines. Software available at http:// www.csie.ntu.edu.tw/~cjlin/libsvm