Objects Recognization Based on On-line Machine Learning
Project Status Report for CIS 519

Abstract

So far, we attempted to use following method described in this report to recognize objects (various kinds of balls in our project) in the given images. The first step is using Circular Hough Tansform (CHT) to detect the most possible region that contains the ball which is datasets preprocessing step. The second step contains techniques to extract feature from the selected region. In the third step, neural network is applied on the extracted features to classify the given instances. Several training/testing experiments have be carried out to show the performance of this method.

1. Introduction

This report presents an attempt of objects recognition. We decided to use images of four kinds of balls from Caltech 256(Griffin, G. Holub, AD. Perona, P.) as our dataset, which contains 98 images of golf in the folder “088.golf-ball”, 174 in “193.soccer-ball”, 104 in “017.bowling-ball” and 98 in “216.tennis-ball”.
Primary tasks for this project:

1. Preprocess the datasets and extract the picture patches with different labels. So far, CHT was applied to test the geometric feature of the balls.
2. Based on machine learning method (e.g. Neural Network) to train the datasets.
3. In the test part, input a test image, the algorithm should detect balls in the image and label the detected ball based on the trained model.

2. SVM learning

Support vector machine(SVM) is one of basic learning algorithm that most widely used to solve object recognition problems (Navneet D., 2005),(Massimiliano P., 1998). In our case, we applied one-class SVM first and extend it to multi-class to train the dataset with several different labels.

2.1. One-Class SVM

Given a set of instances which belongs to either of two classes, a SVM classifier finds the optimal hyperplane leaving the largest possible fraction of instances of the same class on the same side, while maximize the distance of either class from hyperplane, by maximize the $J(\alpha)$ in 1.

$$J(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j \langle x_i, x_j \rangle \quad (1)$$

s.t. $\alpha_i \leq 0 \forall i$, $\sum_i \alpha_i y_i = 0$, where α_i is the constraints weight scaler, and $\langle x_i, x_j \rangle$ is a scaler given by the kernel function.
While applying SVM algorithm, choosing proper kernel is essential to train the classifier. We used two different kernels to train the dataset, which are Gaussian kernel, linear kernel, and drew the Receiver Operating Characteristic(ROC) curve respectively. The result are shown in the figure (1,2). As shown in the figure, the two kernels give similar result while Gaussian kernel provides a faster speed to converge.

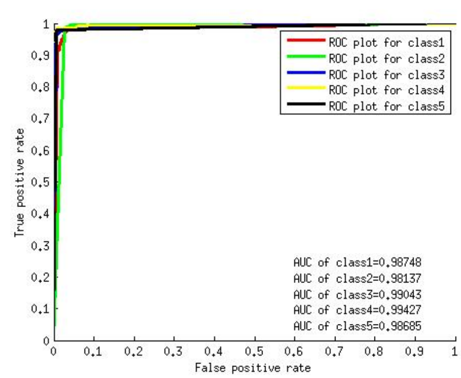

Figure 1. ROC curve of SVM with Gaussian Kernel

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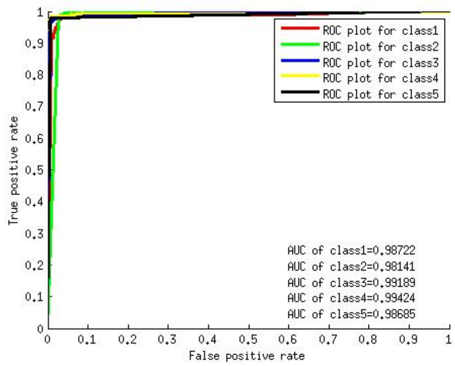

Figure 2. ROC curve of SVM with Linear Kernel

2.2. Multi-Class SVM

Traditional SVM algorithm only solves 2-classes problems. However, detecting ball object in a image should be able to tell whether there is a ball and figure out the type of the ball object, which is a multi-class classification problem. Therefore, one-vs-rest is introduced for solving multi-class problem.
Given a dataset with k different labels, k different one-class SVM classifiers is trained for each class. When training for individual class, the instances that belongs to this class are labeled as 1, and all the others are labeled as 0. A new instance should be predicted as in the class which gives the largest scores value.

2.3. Grid Search

3. result

3.1. Learning Curve

To evaluate our SVM classifier, we run our classifier through 10-fold cross validation and drew the learning curve in figure (**??**) to show the performance versus the number of training examples.

Acknowledgments

This project is supported by Upenn CIS 519. Thanks Eric Eaton and Xiaoxiang Hu for their instruction. Thanks MATLAB for providing some many useful toolbox.

References

Massimiliano P., Alessandro V. Support vector machines for 3d object recogintion. pp. 637–646, 1998.

Navneet D., Bill T. Histograms of oriented gradients for human detection. pp. 886–893, 2005.