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. Model Details

2.1. Overview of the Method

The method for ball recognization is shown in Figure 1. Ball recognization can be considered as the problem of detecting the interested region (ball region) in the image, then fetch features inside the interested region as input features for next step. Then label the interested region based on the machine learning classifier (e.g. Neural Network).

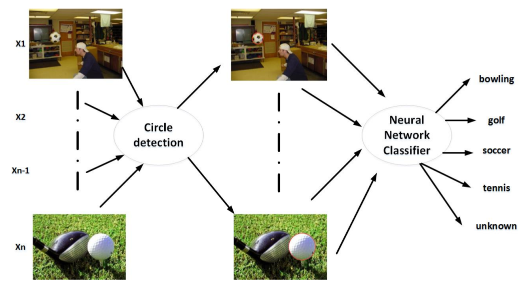

Figure 1. Methodology Overview

2.2. Circle Detection

At the beginning, we considered using corner detection directly on the original image to extract features. However, extracting the corner feature based on the Harris Corner Detection and Adaptive Non-maximal Suppression method(Brown et al., 2005) is not so helpful for following reasons: Firstly, different pattern could be find in a single kind of balls so that geometric corner feature couldn’t provide enough information for clssifying; Secondly, the complicated background could generate large amount of features which are irrelevant to the ball.

During building the training set, the area can be located by either circle detection algorithm or manually selection. However, when classifying a ball in a new image, the circle area has to be detected automatically. Several methods for circle detection are studied in the last few years,(Atherton T.J., 1999),(Victor A., 2006),(D’Orazio T., 2004). One of the robustest approach is Circle Hough Transform(CHT), which takes the image M and desired radius range $[r_{min}, r_{max}]$ as inputs and return the positions of circle centers. The algorithm could be presented in Algorithm 1. In our case, we use the log phase for the accumulator which is

$$\phi_{m,n}^{logr} = 2\pi\Big(\frac{\log\,[\sqrt{(m-i)^2+(n-j)^2)}] - \log r_{min}}{\log r_{max} - \log r_{min}}\Big) \tag{1}$$

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Algorithm 1 Circle Hough Transform

Input: image I, radius range $[r_{min}, r_{max}]$
Initialize accumulator matrix $M = 0$.
for each edge point(i, j) in image I **do**
  for each point (m, n) in image I **do**
    if $r_{min}^2 < (m-i)^2 + (n-j)^2 < r_{max}^2$ **then**
      $M(m, n) = M(m, n) + \phi_{m,n}$
    end if
  end for
end for
Return: positions of local maximum points in accumulator matrix M

While applying CHT method, the sensitivity factor is often introduced, which is a scaler in $[0, 1]$. A higher sensitivity factor helps in detecting weaker and partially obscured circles, however, increases the risk of false detection. In our case, we increased the sensitivity gradually until the first circle is detected to decrease the risk of false detection and miss detection.

2.3. Results

Figure 2 are some results of our implementation of corner detection, red dots are the detected corners.

Several results of applying our circle detection algorithm on Caltech256 dataset are shown in Figure 3.

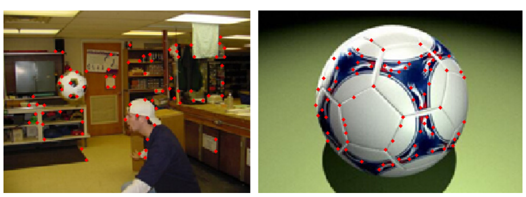

Figure 2. Corner Detection Results

3. Work for Next Stage

3.1. Reconstruct the dataset

In order to introduce neural network into this problem, the training date set need to be normalized to a $n - d$ matrix, where n is the number of training instance and d is the number of pixels. The idea is to resize the intersted area into a particular size, convert the resized image into grey scale and reshape the pixel information into a vector for each circle we found in the circle detection step. Then construct a binary label vector manually according to which kind of ball each instance belongs to.

Figure 3. CHT Detection Result

3.2. Neural Network learning and Deep learning

Given all the dataset and the labels, train the classification model by Neural Network learning and Deep learning with cross validation and try to figure out which method is better for ball classification problem. To evaluate the performance of each learning methods, we plans to compute the overall accuracy and precision, recall for each class and plot the ROC curve.

3.3. HOG and SVM

So far, CHT has been used to detect the circle, however the result is unreliable in some cases. Inspired by paper presented(Dalal & Triggs, 2005) by Navneet Dalal and Bill Triggs, we may try the method described in the paper. The interested region will be labeled manually for the training data. HOG features can be extracted from the interested region. Then SVM or other classifier will be applied to train the learning model.

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