South China University of Technology

The Experiment Report of Machine Learning

SCHOOL: SCHOOL OF SOFTWARE ENGINEERING

SUBJECT: SOFTWARE ENGINEERING

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Face Classification Based on AdaBoost Algorithm

Abstract— In this paper, we extract Normalized Pixel Difference (NPD) features from images to make a face detector, the algorithm used is AdaBoost, and the base learner is decision tree. We also discuss the experimental results in the paper.

I. INTRODUCTION

Face detection is a computer technology being used in a variety of applications that identifies human faces in digital images [1]. Face detection is the first step in face analysis. The problem is to confirm whether there is a human face in the image. If it exists, it will locate the face. Face detection is widely used in the field of application, which is one of the important steps to realize machine intelligence.

NPD feature is computed as the difference to sum ratio between two pixel values, inspired by the Weber Fraction in experimental psychology [2]. The new feature is scale invariant, bounded, and is able to reconstruct the original image. Second, we propose a deep quadratic tree to learn the optimal subset of NPD features and their combinations, so that complex face manifolds can be partitioned by the learned rules.

AdaBoost algorithm is a fast face detection algorithm proposed in 1995. It can be used in conjunction with many other types of learning algorithms to improve performance. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier [3].

In this experiment, we implement the AdaBoost algorithm based on single decision tree to detect the face, and the different experimental parameters were compared and discussed, finally obtained a satisfactory experimental results, we will describe the experimental principle and the steps we detail below, and discuss some of the results.

II. METHODS AND THEORY

The whole experiment is divided into two steps:

1) Read data set data. The images are supposed to converted into a size of 24 * 24 grayscale

2) Processing data set data to extract NPD features.

3) Add the class label to the data set, dividing dataset into training set and validation set.

4) Processing the image data to get the NPD features of the image.

5) Implementation of AdaBoost algorithm

6) Training model, calculating error, adjusting parameters, and obtaining experimental results

Next, let's talk about the theory used in the experiment.

A. Normalized Pixel Difference (NPD) feature

The NPD feature be-tween two pixels in an image is defined as

$$f(x, y) = \frac{x - y}{x + y}$$

The NPD feature measures the relative difference between two pixel values. The sign of f(x, y) indicates the ordinal relationship between the two pixels x and y, and the magnitude of f(x, y) measures the relative difference. The NPD features has the following advantages:

1) NPD feature evaluation is very fast, and only one memory call can be used to produce results.
2) using a pre scale detection template can easily respond to multiple dimensions of face recognition
3) there is no need to classify the types of faces in advance
4) can do a variety of difficult identification

B. AdaBoost Algorithms

Defining loss function as exponential loss function:

$$L(y, f(x)) = exp(-yf(x))$$

According to the additive model, the classification function of the m times:

$$f_m(x) = f_{m-1}(x) + \alpha_m G_m(x)$$

Among them, the α_m is the combination coefficient of the base classifier $G_m(x)$. AdaBoost uses stage wise forward to minimize the loss function, and solves α_m sub-model:

$$\alpha_m = \frac{1}{2}\log\frac{1 - e_m}{e_m}$$

Among them, e_m is the classification error rate of $G_m(x)$. The distribution of data centralization of the training data in the m+1 round:

$$D_{m+1} = (w_{m+1,1}, \cdots, w_{m+1,i}, \cdots, w_{m+1,N})$$

$$w_{m+1,i} = \frac{w_{m,i}}{Z_m} exp(-\alpha_m y_i G_m(x_i))$$

Among them, Z_m is normalization factor:

$$Z_m = \sum_{i=1}^{N} w_{m,i} * exp(-\alpha_m y_i G_m(x_i))$$

Then the final classifier is obtained:

$$sign(f(x)) = sign(\sum_{m=1}^{M} \alpha_m G_m(x))$$

The specific algorithm flow is as follows:

Algorithm 1: Adaboost

Input: $D = \{(\mathbf{x}_1, y_1), ..., (\mathbf{x}_n, y_n)\}$, **where** $\mathbf{x}_i \in X, y_i \in \{-1, 1\}$

Initialize: Sample weight distribution $D_1 = \frac{1}{n}$

Train a base learner $h_1(\mathbf{x})$ with D_1

for m=2,3,...,M **do**

  Update the sample distribution D_m, to make the wrong predictive samples more important

  Train a new base learner $h_m(\mathbf{x})$ with D_m

end

Output: $H(\mathbf{x}) = \sum_{m=1}^{M} \alpha_m h_m(\mathbf{x})$

III. EXPERIMENT

A. Dataset

1000 pictures, of which 500 are human face RGB images, the other 500 is a non-face RGB images.

Fig. 1. Dataset

For this paper, we used sklearn.model_selection. train_test_split function to divide dataset into training set and validation set, the parameter "test_size" is 0.33.

B. Implementation

a. Data preprocessing

First, we need to use the Image module in the PIL library to read the picture and convert it into a grayscale map.

Fig. 2. Images after grayscale and adjusting the resolution

We use functions in feature.py to extract NPD features of images. These functions are provided by experiments, so we are not wasting space on this. After NPD extracting, the dataset turn out to be an (500, 165600) ndarray.

Then, we add the class label [1,-1] to the data set, 1 for face and -1 for nonface, divided dataset into training set and validation set using "sklearn.model_selection.train_test_split" function, the parameter "test_size" is 0.33.So we got (330, 165600) ndarray validation set and (670, 165600) ndarray training set.

The details of the data preprocessing are as follows:

TABLE 1
DATESET SPLITING

Selection of validation	hold-out
Training set size	(670, 165600) ndarray
Validation set size	(330, 165600) ndarray

b. Implementation of Adaboost

Complete the algorithm based on the expressions introduced in algorithm 1 and part II, specific code is in the uploaded files.

c. Experimental result

On the basis of the implementation of the AdaBoost algorithm, we have done the following experiments on the algorithm:

1) change the number of the base classifier, and observe the change of error rate on the validation set and the training set

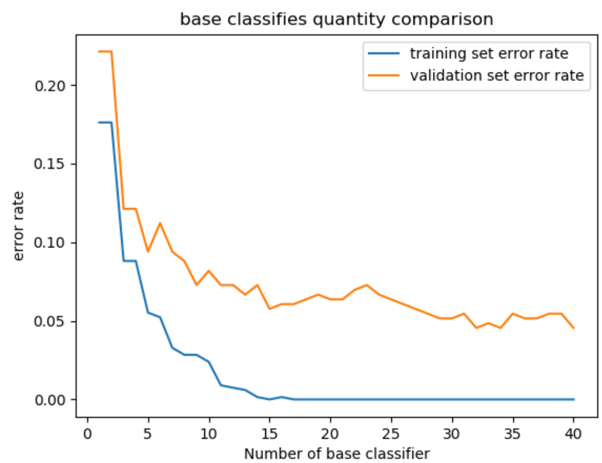

Fig. 3. Base classifies quantity comparison

2) the value of e_m during the iteration

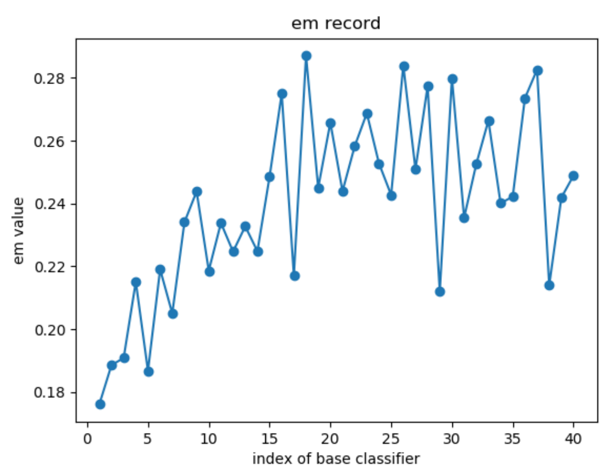

Fig. 4. e_m record during training

3) changes in the weight α_m of the base classifier during a training process

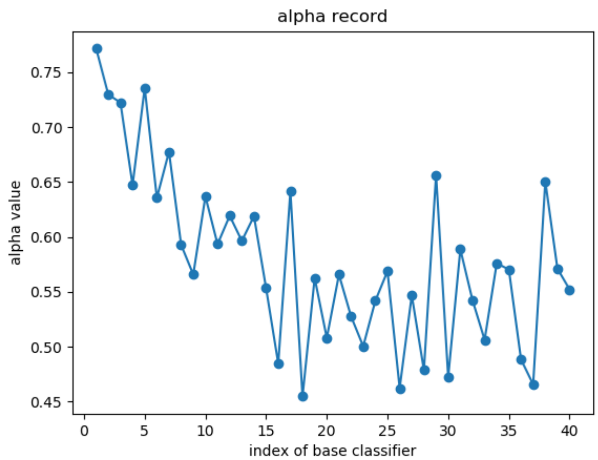

Fig. 5. α_m record during training

4) analyze the high error rate pictures and find out the possible reasons

We find a representative example from the misclassified picture:

Fig. 6. Error classification picture example

We can see that the face in this picture is blocked, so our model also needs to be improved for this situation.

5) Experimental report

TABLE 2
EXPERIMENTAL REPORT

	Precision	recall	f1-score	support
face	0.94	0.97	0.95	160
noface	0.97	0.94	0.96	170
avg / total	0.96	0.95	0.95	330

IV. CONCLUSION

In this experiment, we implement the AdaBoost algorithm based on single decision tree to detect the face, and the different experimental parameters were compared and discussed, finally obtained a satisfactory experimental results

From the Fig. 3, we can find out that with the increase of base classifiers, the error rate showed a decreasing trend on the whole, this is consistent with the principle of our algorithm, because we just as simple classifier depth decision tree 1, but with the increase of the validation set error rate fluctuation and the number of base classifiers, the training set error rate when base classifiers the number is about 20 has reached stable, considering we mainly focus on the validation set effect, so the number of base classifiers we finally adopted for 40.

From the Fig. 4 and Fig 5, we can find out that the e_m of the base classifier is fluctuant, and the first base classifier has the best effect, which accounts for the largest proportion. As for α_m , because it is converted from e_m, it is clear that the maximum weight of the first base classifier is reasonable.

To sum up, this experiment enables us to recognize face recognition, and enables us to master the AdaBoost algorithm. What's more valuable is that we have exercised teamwork ability. Thank the teacher for arranging this experiment, and let us have the opportunity to improve ourselves.

References:

[1] wikipedia.org. Face detection [EB/OL]. https://en.wikipedia.org/wiki/Face_detection
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[3] wikipedia.org. AdaBoost [EB/OL]. https://en.wikipedia.org/wiki/AdaBoost