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—
Face detection is the process of determining the location of human faces in an image. Like human visual system, a face detection system should also be capable of achieving the detection task irrespective of illumination, absence of texture, orientation and camera distance. Detecting faces in heterogeneous, infrared and thermal images is a challenging job due to variation in texture, orientation, lighting condition, intensity etc. Many researchers have worked and proposed various methods for visible faces in the domain of face detection. This paper attempts to improve the accuracy of adaboot algorithm which was basically designed for detecting visible faces, can now be used to detect heterogeneous faces by applying various image enhancement techniques. Attempts have been tested on test image data set. The experimental results are found to be encouraging.

I. INTRODUCTION

Ensemble learning is to create multiple models and combine results from models, and it has attracted much research attention. If the center of attention is classification, ensemble learning could be understood as follows: It constitutes a group of classifiers first and then aggregates classification results or predictions from these member classifiers. For an unseen sample, it inputs the sample to member classifiers, collects predictions from member classifiers, and outputs the final prediction based on some methods.

AdaBoost (Adaptive Boosting) is one of the most popular ensemble learning algorithms. It has been applied to various applications such as face classification, natural language processing, network security, health care, computer vision, wearable computing, and intelligent transportation systems. Ensemble learning requires diversity. AdaBoost algorithm creates diversity by manipulating training sets, and it operates on training sets composed of hard-to-classify samples as the process proceeds.

II. METHODS AND THEORY

In this section, we will introduce the theory of adaboost algorithm. The error rate of Its applications on face classification will be present.

A. NPD feature

a image feature called Normalized Pixel Difference (NPD) is used. NPD feature is computed as the difference to sum ratio between two pixel values, inspired by the Weber Fraction in experimental psychology. The new feature is scale invariant, bounded, and is able to reconstruct the original image. Only a single soft-cascade classifier is needed to handle unconstrained face detection. Furthermore, we show that the NPD features can be efficiently obtained from a look up table, and the detection template can be easily scaled, making the proposed face detector very fast.

The Normalized Pixel Difference feature between two pixels in an image is defined as

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

where $x, y \geq 0$ are intensity values of the two pixels, and $f(0,0)$ is defined as 0 when $x=y=0$.

B.adaBoost

Every iteration generates a new base learner $\mathrm{h}_m(x)$ and its importance score α_{m}

$$\mathrm{H}(x)=sign(\sum_{m=1}^{m}\alpha_m h_m(x))$$

Base learner

$$h_m(x): x \mapsto \{-1,1\}$$

$$h_m(x) = sign(w^T x)$$

$h_m(x)$ is a nonlinear function, so the Adaboost can deal with nonlinear problem. Error rate is

$$\varepsilon_m = p(h_m(x_i) \neq y_i) = \sum_{i=1}^{n} w_m(i) II(h_m(x_i) \neq y_i)$$

It should be $\varepsilon_m < 0.5$, or the performance of Adaboost is weaker than random classification. Still, make the base learner with lower ε_m more important

$$\alpha_m = \frac{1}{2}\log(\frac{1}{\varepsilon_m + \delta} - 1)$$

So the final weights ω_m is

$$\omega_{m+1}(i) = \frac{\omega_m(i)}{Z_m} e^{-\alpha_m y_i h_m(x_i)}$$

Where $i = 1,2,...,n$ and $Z_m = \sum_{i=1}^{n} \omega_m(i) e^{-\alpha_m y_i h_m(x_i)}$

III. Experiment

A. Data set :This experiment provides 1000 pictures, of which 500 are human face RGB images, the other 500 is a non-face RGB images. We divide it into training set and validation set and choose 800 for our training set and validation.

B. Implementation Details

The experiment step is as follow

1. Read data set data. The images are supposed to converted into a size of 24 * 24 grayscale, the number and the proportion of the positive and negative samples is not limited, the data set label is not limited.
2. Processing data set data to extract NPD features. Extract features using the NPDFeature class in feature.py. We deal with pickle function library dump () to save the data in the cache, then can used load () function reads the characteristic data from cache

3. The data set is divided into training set and validation set, this experiment does not divide the test set.

4. Write all AdaboostClassifier functions based on the reserved interface in ensemble.py. The following is the guide of fit() function in the AdaboostClassifier class:

4.1 Initialize training set weights ω, each training sample is given the same weight.

4.2Training a base classifier , which can be sklearn.tree library DecisionTreeClassifier(note that the training time we need to pass the weight ω as a parameter).

. 4.3 Calculate the classification error rate ε of the base classifier on the training set.

4.4 Calculate the parameter according to the classification error rate ε .

4.5 Update training set weights ω .

4.6 Repeat steps 4.2-4.6 above for iteration, the number of iterations is based on the number of classifiers.

5. Predict and verify the accuracy on the validation set using the method in AdaboostClassifier and use classification_report () of the sklearn.metrics library function writes predicted result to report.txt .

As for initialization parameter we choose set all weights ω into $1/feature\_size$.The table 1 one show the parameter we choose in this lab.

TABLE 1 PARAMETER OF ADABOOST

number of classifiers	7
Parameter δ	$\delta = 1e-6$
number of train set and validation set	800

Fig 1.shows the accuracy on the validation set using the method in AdaboostClassifier.

```
begin
0 th acc: 0.900000
1 th acc: 0.840000
2 th acc: 0.750000
3 th acc: 0.865000
4 th acc: 0.845000
5 th acc: 0.800000
6 th acc: 0.855000
final acc 0.925000
end
```

Fig 1 the accuracy on the validation set using the method in AdaboostClassifier

IV. Conclusion

We have achieved a fast and accurate method for face detection in cluttered scenes. First, a simple feature called NPD is used, which has properties of scale invariance, boundedness, and reconstruction ability. Second, we use AdaBoot algorithm achieved Adaboost Classifier and iterate on the number of classifiers which is seven. As a result, a single AdaBoost classifier is able to achieve promising results for face detection with large pose variations and occlusions. The result of accuracy is satisfactory.