Face Detection and Recognition Based on an Improved Adaboost Algorithm and Neural Network

Haotian Zhang*, Jiajia Xing, Mutian Zhu, Dan Wu, Zheyu Yang

Department of Engineering and Computing Sciences, New York Institute of Technology, 1855 Broadway, New York, NY 10023-7692, USA

School of Overseas Education, Nanjing University of Posts and Telecommunications, Nanjing, Jiangsu, 211106, China

*Corresponding author email: zhtpandog@foxmail.com

Abstract In recent years, face detection and face recognition based on images have been widely used in various fields. This paper focuses on face detection methods based on the Adaboost algorithm, optimizes and improves the weight updating rules of the Adaboost face detection algorithm. Results indicate that the optimized Adaboost algorithm has not only been greatly improved in computing speed and face positioning effect, but also been integrated into a neural network model for face identification. It is found that not only faces of poor image quality can be recognized, the computing speed and anti-interference ability are better than traditional face detection and recognition algorithms. Therein, the comprehensive face recognition rate in ORL database reaches more than 98%. The recognition rate is high.

1. INTRODUCTION

Face detection is a key technology in face information processing. Reliable face detection is a premise of efficient face recognition (Turk M and Pentland A, 1991; Sirovich L and Kirby M, 1987). Among them, the use of face information mainly includes two aspects: face detection and face recognition. Face detection is the first link in the extraction of face information, whose detection performance will directly affect the extraction of face information and further affect subsequent face recognition. In recent years, face detection and face recognition technology based on static images and dynamic videos has been brought to great attention in the field of pattern recognition and computer vision (Reed T R and Du Buf J M H, 1993; Chen C H and Pan L F, 1993; Brooks R A, 1983; Pope A R, 1994; Chin R T and Dyer C R, 1986).

Generally speaking, current face detection methods can be divided into two types: detection based on knowledge and detection based on statistics (Brunelli R and Poggio T, 1993). Face detection based on knowledge mainly regards face as a combination of organ features according to prior knowledge. It detects faces based on features of eyes, eyebrows, mouth, nose and other organs, as well as their relative geometric positions. Face detection based on statistics, however, regards face as a 2D data matrix and judge whether a face exists or not from similarity, by constructing face pattern space.

This paper carries out an in-depth study into face detection methods based on Adaboost, puts forward an improved the optimized Adaboost algorithm, extracts all face information in an image using this model and integrates it into a neural network model (Brosch T and Tam R, 2015), to detect and recognize various face-containing images (Y. Bourieu and F. Bach, 2010; I. J. Goodfellow and Q. V. Le, 2009; G. E. Hinton, S, 2006; J. Yang and K. Yu, 2009; Marina E. Plissiti and HristophorosNikou, 2011; Q. C. Chen and Q. S. Sun, 2008). Experimental results show that both the face detection and face recognition rates of the optimized Adaboost algorithm integrated into neural network model in this paper are high. Not only images of poor quality can be processed, the computing speed and anti-interference ability are better than traditional face detection and recognition methods.

2. OPTIMIZATION OF THE ADABOOST FACE DETECTION ALGORITHM

The core idea of traditional Adaboost algorithms is aimed at the same training database. Several different weak classifiers are produced in the process of training and some better classifiers are combined into ultimate strong classifiers. The training process only includes:

1. To extract Haar features in an image;
2. To transform the Haar features into corresponding weak classifiers;
3. To select the best weak classifiers from a large number of weak classifiers and combine them into optimal strong classifiers.

However, the data size during face detection and face training is large. Generally each weak classifier has tens of thousands of training samples. When there are many sample objects that are difficult to distinguish in training samples, often as trainings times increase, the weights of indistinguishable sample images will be high and model training will focus on this part of samples. As a result, the training will be too long and over fitting will occur in model results. Therefore, this paper improves the weight updating algorithm in the Adaboost...
training process and judges whether a weight needs to be updated by setting a weight updating threshold. The detailed calculation steps of the optimized model are as follows:

Step 1: To classify and number N training samples, where m face samples are labeled as \( y_i = 1 \) and N-m non-face samples are labeled as \( y_i = -1 \).

Step 2: To initialize the weights of N training samples.

Step 3: In the process of the tth iteration training, select T weak classifiers, and calculate the iteration error sum of T weak classifiers see formula (1) and relative error ratio see formula (2).

\[
\varepsilon_i = \sum_{i=1}^{N} w_i | h_i(x) - y_i |
\]

(1)

\[
\beta_t = \frac{\varepsilon_t}{1 - \varepsilon_t}
\]

(2)

Step 4: In each iteration, calculate the threshold \( HW_t \). When various image weights are updated, if a weight is greater than \( HW_t \) or a sample belongs to a correct class, the weight will no longer be adjusted. Otherwise, when a sample is wrongly classified and the current weight \( D_i \) is smaller than the threshold \( HW_t \) of current iteration, the weight of image should be adjusted. The calculation formulas of weight adjustment expression and threshold \( HW_t \) in each iteration are as follows:

\[
D_{i+1}(x) = \frac{D_i(x)}{Z_t} \left\{ \begin{array}{ll}
e^{-\alpha} & h_i(x) = y_i, D_i(x) \leq HW_t \\
e^{\alpha} & h_i(x) \neq y_i, D_i(x) > HW_t \\
\sum_{i=1}^{N} D_i(x) & \end{array} \right.
\]

(3)

\[
HW_t = \frac{\sum_{i=1}^{N} D_i(x)}{N}
\]

(4)

Where \( Z_t \) is the normalization factor of \( D_{i+1}(x_i) \), generally \( D_{i+1}(x_i) \). \( HW_t \) is the weight updating threshold of the tth iteration.

Step 5: After a model training iteration is completed, several better classifiers will be combined linearly to get strong classifiers. As shown below, they will be connected in series to form a strict cascade classifier.

\[
h_j(x) = \left\{ \begin{array}{ll}
1 & \sum_{i=1}^{T} (\log 1/\beta_i) h_i(x) \geq \frac{1}{2} \sum_{i=1}^{T} \log 1/\beta_i \\
0 & \sum_{i=1}^{T} (\log 1/\beta_i) h_i(x) < \frac{1}{2} \sum_{i=1}^{T} \log 1/\beta_i \\
\end{array} \right.
\]

(5)

3. FACE DETECTION EXPERIMENT ON THE OPTIMIZED ADABOOST ALGORITHM

The above improved Adaboost algorithm is used for face detection. Images of different qualities are tested respectively. Experimental results show that the optimized Adaboost algorithm has better face detection performance. The results are shown in Table 1 below, and part of the face detection results are shown in Fig. (1) below:

<table>
<thead>
<tr>
<th>Real Faces</th>
<th>Detected Faces</th>
<th>Detection Rate%</th>
<th>Loss Rate%</th>
<th>Error Rate%</th>
<th>Image Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>4</td>
<td>80</td>
<td>20</td>
<td>0</td>
<td>Low</td>
</tr>
<tr>
<td>10</td>
<td>10</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>13</td>
<td>13</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>18</td>
<td>18</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>29</td>
<td>29</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Low</td>
</tr>
<tr>
<td>35</td>
<td>35</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>45</td>
<td>38</td>
<td>84.4</td>
<td>16.6</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>50</td>
<td>50</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Low</td>
</tr>
<tr>
<td>70</td>
<td>70</td>
<td>100</td>
<td>0</td>
<td>0</td>
<td>Low</td>
</tr>
<tr>
<td>75</td>
<td>70</td>
<td>93.3</td>
<td>7.7</td>
<td>0</td>
<td>Low</td>
</tr>
<tr>
<td>85</td>
<td>82</td>
<td>96.5</td>
<td>4.5</td>
<td>0</td>
<td>Ordinary</td>
</tr>
<tr>
<td>90</td>
<td>81</td>
<td>90</td>
<td>10</td>
<td>0</td>
<td>Ordinary</td>
</tr>
</tbody>
</table>
The purpose of face recognition is to extract personalized features from face images, so as to identify the identity of a person. A complete face recognition system mainly includes face detection, face standardization, face characterization and face recognition. From the above face detection experiment, we can see that for a given image, the optimized Adaboost algorithm can basically detect all existing faces in an image. In order to fully demonstrate that the optimized Adaboost model can provide favorable values for subsequent face identification, on this basis, this paper probes into a face recognition model based on the optimized Adaboost algorithm integrated into neural network. The face recognition model flows of the optimized Adaboost algorithm integrated into neural network designed in this paper are as follows:

Step 1: First of all, unify pixel sizes of all face training samples as 20*50. Extract each line of pixels according to pixel levels and transform them into a column matrix line by line as input information to train BP neural network model. The detailed network convergence and network structure parameters in the first detection and recognition are shown in Table 2 below:

Step 2: To use the optimized Adaboost algorithm to detect faces in a given image and extract all of them.

Step 3: To process pixels in the extracted face areas in Step 2, according to Step 1.

Step 4: To input face information derived from Step 3 into a neural network model and recognize relevant faces.

Part of the face detection and recognition results of the optimized Adaboost algorithm integrated into neural network model is shown in Fig. (2) below:
Table 2. Key Parameters in Network Training Setting and Network Convergence

<table>
<thead>
<tr>
<th>Network Training Parameters</th>
<th>Network Convergence Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nodes at the first level</td>
<td>1000</td>
</tr>
<tr>
<td>Nodes at the second level</td>
<td>50</td>
</tr>
<tr>
<td>Network target error</td>
<td>1.0e-8</td>
</tr>
<tr>
<td>Network training function</td>
<td>trainrp</td>
</tr>
<tr>
<td>Network training times</td>
<td>21</td>
</tr>
<tr>
<td>Network training time (sec)</td>
<td>9</td>
</tr>
<tr>
<td>Network convergence error</td>
<td>1.26*10^-8</td>
</tr>
<tr>
<td>Network goodness of fit</td>
<td>1</td>
</tr>
</tbody>
</table>

Figure 2. Results of BP Network Model Training Convergence

Figure 3. Face Recognition Results of the Optimized Adaboost Algorithm Integrated into Neural Network Model. Fig. (a) The detection and recognition of different expressions of the same face; Fig. (b) The detection and recognition of different faces and expressions.
The above optimized Adaboost model integrated into neural network is used for face recognition. The face data base involved is ORL face data base from Olivette Lab. There are a total of 400 face images in ORL database. This database includes 40 persons and 10 face images of each. The resolution of each image is 92 pixels by 112 pixels.

In order to ensure the generality of experiment, 4 images of each person are selected and made into training samples during experiment. The remaining face images of each person (6) are made into test samples. During training, updating rules, it is found that not only faces of poor image quality can be recognized, the computing speed and anti-interference ability are better than traditional face detection and recognition algorithms. Therein, the comprehensive face recognition rate in ORL database reaches more than 99%. The recognition rate is high.

<table>
<thead>
<tr>
<th>Test Times</th>
<th>Training Samples</th>
<th>Test Samples</th>
<th>Recognition Accuracy</th>
<th>Recognition Accuracy of Test Samples</th>
<th>Comprehensive Recognition Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>160</td>
<td>240</td>
<td>0.9937</td>
<td>0.9791</td>
<td>0.9849</td>
</tr>
<tr>
<td>2</td>
<td>160</td>
<td>240</td>
<td>0.9937</td>
<td>0.9791</td>
<td>0.9849</td>
</tr>
<tr>
<td>3</td>
<td>160</td>
<td>240</td>
<td>0.9937</td>
<td>0.9958</td>
<td>0.9950</td>
</tr>
<tr>
<td>4</td>
<td>160</td>
<td>240</td>
<td>0.9875</td>
<td>0.9958</td>
<td>0.9925</td>
</tr>
<tr>
<td>5</td>
<td>160</td>
<td>240</td>
<td>0.9875</td>
<td>0.9875</td>
<td>0.9875</td>
</tr>
</tbody>
</table>

5. CONCLUSION

By optimizing and improving the weight updating rules of the Adaboost face detection algorithm, this paper prevents model training from focusing on difficult samples at the later stage and too large weights of difficult samples, caused by the existence of difficult training samples. By setting new weight updating rules, overmatching is avoided. Results show that the optimized Adaboost algorithm has not only been greatly improved in computing speed and face positioning effect, but also been integrated into a neural network model for face identification. It is found that not only faces of poor image quality can be recognized, the computing speed and anti-interference ability are better than traditional face detection and recognition algorithms. Therein, the comprehensive face recognition rate in ORL database reaches more than 99%. The recognition rate is high.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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