Research of Human Appearance Level Quantification Algorithm Based on BP Neural Network

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Abstract. BP neural network has strong mistake tolerance and unsupervised speaker adaptation, so it has a wide range of applications in the field of pattern recognition. In this paper, an appearance level quantification algorithm based on BP neural network to extract face geometric features is proposed. We use 30 feature distances corresponding to facial features as the quantitative factor to calculate the appearance level and predict the appearance scores of the given face images.

1. Introduction

Beauty is the unique ability of human beings to perceive the appearance of human face. Beauty can bring joy to the human heart and can strongly stimulate human feelings. Everyone has a heart of loving beauty [1]. In social life, beauty can bring many social and economic benefits [2]. In contemporary society, people’s pursuit of beauty has led to the rapid development of the clinical plastics and cosmetics industry. Human beings have been studying beauty for thousands of years. In ancient China, there was the definition of beauty in the so-called "three foreheads and five eyes". Europe also had the "golden ratio" and other conditions for the distribution of facial features of beautiful faces [3]. However, what is the definition of beauty, there is always no standardization to standard it.

With the development of science and technology, there are more and more studies based on the beauty of human beings. Humans are eager to find a standard to define beauty. Cognitive Psychology through a large number of research experiments, has found that human beings have a high degree of consistency in their cognition of beauty in the recent years, and this consistency has nothing to do with culture, race, gender, and age [4].

This paper proposes a BP neural network appearance value quantification algorithm. By extracting the geometric features of the face and using the appearance value score data set SCUT-FBP5500 training model, we finally want to achieve the goal of quantifying the appearance values of different faces.

2. BP neural network

2.1. Mathematical model of BP neural network

The structure diagram of the bp neural network is as follows:
Figure 1. BP neural network model.

As one of the Artificial Neural Network, BP neural network consists three parts, the Input Layer, the Hidden Layer, and the Output Layer, each layer contains different amount of neurons [5]. BP neural network is divided into two types: hierarchical network and interconnected network. According to the differences between the actual output and the expected output, the multi-layer feedforward network with error correction for each layer of the network is corrected by the backward and forward layers, which is called BP neural network [6]. The information is forwarded and the error is reversed in such a way that the result is as close as possible to the expected value, which supplies a new method to solve the problems with multi-factor, complexity, randomness and nonlinearity [7].

The main idea of the back propagation algorithm is to divide the computing process into two parts: the first part (forward propagation process), the actual output value of each node of the input node is calculated layer by layer from the input layer to the output layer, the state of each layer of neurons only influences the state of neurons from the next layer. The second part (back propagation process), if the excepted output value is not gained from the output layer, recursively calculate the errors between the actual output value and the expected output value layer by layer. Then correct the front layer weights based on these errors and tends to minimize the error signal [8]. It gradually approaches the target value by continuously calculating the network weights and deviations in the direction of the decline of the slope gradient of the error function. Each change of weight and error is proportional to the effect of network loss [9].

It is assumed that the number of elements of the input layer, the intermediate layer, and the output layer are N, L, and M. X = (x_0, x_1, ..., x_{N-1}) is the input vector of the network, H = (h_0, h_1, ..., h_{L-1}) is the output vector of intermediate layer, Y = (y_0, y_1, ..., y_{M-1}) is the actual output vector of the network, and D = (d_0, d_1, ..., d_{M-1}) is used to represent the target output vector of each mode in the training set. The weight of the output node \( i \) to the hidden node \( j \) is \( W_{ij} \) and the weight of the hidden node \( j \) to the output node \( k \) is \( W_{jk} \). Besides, \( \theta_k \) and \( \phi_j \) are used to express the thresholds of the output unit and the hidden unit respectively [10].

The transfer function which is also called as the stimulus function is a function that reflects the intensity of the stimulus of the lower layer input to the upper node. It is generally taken as the continuous value function in (0,1): Sigmoid [11], which is:

\[
f(x) = \frac{1}{1 - e^{-x}}
\]

The error function is:

\[
E = \frac{1}{2} \sum_{j=1}^{M} (d_j - y_j)^2
\]
The output of each node in the hidden layer and output layer is:

\[ h_j = f\left(\sum_{i=0}^{N-1} V_{ji}x_i + \phi_j\right) \]  \hspace{1cm} (3)

\[ y_k = f\left(\sum_{j=0}^{L-1} W_{kj}h_j + \theta_k\right) \]  \hspace{1cm} (4)

The BP algorithm uses the gradient descent method to adjust the weight:

\[ W_{ij}(n+1) = W_{ij}(n) + \eta \delta_j x_i \]  \hspace{1cm} (5)

In this function, \( j \) is the sequence number of the node, \( i \) is the sequence number of the hidden layer or the input layer node. \( x_i \) is the output of node \( i \) or an external input; \( \eta \) is called the learning rate and \( \delta_j \) is the error term [12].

2.2 Constructing BP neural network model based on appearance value quantification algorithm

(1) Using SCUT-FBP5500 as the data set of this paper, the trained model is used to capture 68 key points of each face image, and 30 feature distances related to appearance values are extracted based on these key points.

(2) The feature distances and corresponding appearance value score labels of each picture are entered into the BP neural network, 80% of the data sets are taken as the training set, and the remaining 20% is used as the test set to test the training model.

(3) We would select different learning rates, different iterations and compare the relative error of each test sample to compare the accuracy of the test, then draw a chart and finally draw conclusions.

3. Experimental data

This paper uses the face value data set SCUT-FBP5500 released by South China University of Technology. The data set has a total of 5,500 positive faces and an age distribution of 15-60, all of which are natural expressions. It contains different gender distributions and ethnic distributions (2,000 Asian women, 2,000 Asian men, 750 Caucasian men, 750 Caucasian women), these data comes from Data Hall, US Adult database, etc. Each figure was scored by 60 people and rated as 1 to 5 in total. The 60 people were aged 18 to 27 years old and were young [13], suitable for model research based on appearance/shape and so on.

![Figure 2. SCUT-FBP5500 appearance value data set.](image)
We use the trained model to capture and mark 68 key points on the face of each picture:

![Image of labeled face](image)

**Figure 3.** Labeling of 68 key points of the human face.

Extract 30 feature distances related to appearance values by the distance of the key points:

| Number | Remarks(width)                        | Related points | Number | Remarks(height)                           | Related points |
|--------|---------------------------------------|----------------|--------|-------------------------------------------|----------------|
| 1      | Center spacing between the eyes        | 38→44          | 16     | Left eye and eyebrow distance             | 20→38          |
| 2      | Left eye width                         | 37→40          | 17     | Right eye and eyebrow distance            | 25→45          |
| 3      | Right eye width                        | 43→46          | 18     | Left eye height 1                         | 38→42          |
| 4      | Left eyebrow width                     | 18→22          | 19     | Left eye height 2                         | 39→41          |
| 5      | Right eyebrow width                    | 23→27          | 20     | Right eye height 1                        | 44→48          |
| 6      | Eyebrow distance                       | 22→23          | 21     | Right eye height 2                        | 45→47          |
| 7      | Inner eye corner spacing               | 40→43          | 22     | Lip thickness 1                           | 51→59          |
| 8      | Outer eye corners spacing              | 37→46          | 23     | Lip thickness 2                           | 53→57          |
| 9      | Face width                             | 2→16           | 24     | Nasal height                             | 28→34          |
| 10     | Nose width                             | 32→36          | 25     | Eye to nose                              | 28→31          |
| 11     | Face width over the nose               | 4→14           | 26     | Tip to mouth                             | 31→67          |
| 12     | Face width over the lips               | 5→13           | 27     | Mouth to chin                            | 31→9           |
| 13     | Mouth length                           | 49→55          | 28     | Eye to chin                              | 28→9           |
| 14     | Over the lip face width                | 6→12           | 29     | Left ear length                          | 1→3            |
| 15     | Chin wide                              | 7→11           | 30     | Right ear length                         | 17→15          |
4. Experimental results and discussion

4.1 Model judging criteria

We divide the data set into training set and test set, then extract 30 feature distances of each picture and enter them into the BP neural network as the input node, and use the appearance value score label as the output node to train the appearance value BP neural network. The accuracy of the test set is judged the average relative error. The formula is as follows [14]:

\[ \mu = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{|d_i - y_i|}{y_i} \right) \times 100\% \]  \hspace{1cm} (6) 

4.2 Experimental result

For the 5,500 image samples in SCUT-FBP5500, 80% is taken as the training sample and 20% is taken as the output sample. The learning rate is 0.05, the number of iterations is 2000, and the average relative error \( \mu = 21.82\% \).

4.3 Experimental analysis

In view of the above experimental results, we change the learning rate in order to compare the relative error. According to experience, the learning rate is optimal between 0.01 and 0.1, and the results obtained by changing the learning rate parameters are as follows:

![Figure 4. Learning rate - relative error curve](image)

After comparison, we found that the relative error fluctuation is relatively stable when the learning rate is between 0.04 and 0.08. When the learning rate is 0.07, we get the relatively lowest error rate \( \mu = 20.93\% \). In this case, we continue to change the number of iterations of training, taking the range of 1000~10000 times, and the results are as follows:

![Figure 5. Iteration times - relative error curve](image)

We find that by adjusting the number of iterations, the average relative error does not change much, and it always fluctuates up and down within 1%. With the increase of the number of iterations, the
relative error value tends to be convergent. When the learning rate is 0.07, when the number of iteration times is 9000, we get the relatively lowest error rate $\mu = 20.19\%$.

5. Conclusion

Through the analysis of the results, we found that the correlation between the 30 key feature distances of the human face and the appearance value score label is close to 0.8, which shows that there is a lot of relevance between the geometric features of human face and the appearance value. BP neural network has better self-learning, self-adaptive ability and certain promotion ability, but when it faces complex optimization objective function, when the output of the neuron approximates the real value, easily be trapped in the local optimization. The promotion and generalization capabilities need to be further improved. Therefore, the follow-up work can improve the BP neural network, add other variable factors that affect the appearance value, select a more detailed and accurate model, further improve the accuracy of the appearance level, and train a Human Appearance Level Quantification System that is more in line with human aesthetics and more intelligent.

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