RESEARCH ON FACE RECOGNITION ALGORITHM UNDER COMPLEX CONDITIONS

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Abstract:-

This paper presents a face model based on Bayesian networks. The main idea is to establish a Bayesian network model based on the cognitive theory in daily life. The input of the network is the feature of facial organs on the face (that the organs have relevance in the model), and the output is the specific type of the face. Then the feature vectors of facial organs are extracted according to a certain algorithm. Finally, the specific categories are calculated by Gauss distribution and joint tree algorithm. Experimental results show the algorithm has excellent recognition effect.

Keywords:-*Face recognition Bayes illumination, Bayes, Illumination*

BACKGROUND

Face recognition research has a long history. Since last century, people have been exploring the face recognition technology. For face recognition, input images usually have two situations: frontal and multi pose. Early face recognition technology is usually done on frontal faces. In practical applications, there is often a change in the angle between the face and the photographing equipment, so the face image collected is not a positive one, but a face image of a variety of posture. Multi pose face images are stretched or compressed in different parts of the face because of the projection deformation. This makes the face image greatly deformed, and it will be very difficult to use the traditional face recognition technology for face recognition. When the training sample is single view, the recognition rate of multi pose face will drop sharply. Therefore, face recognition has become a hot research topic in the field of face recognition. It has important theoretical and practical value.

1. Recognition principle

We choose the local two element model algorithm (LBP) to roughly detect the position of the face in the image, and then select the active shape model (ASM) to extract the facial features on the face, such as eyebrows, eyes, nose, mouth and other facial features. After that, histogram equalization algorithm is used to eliminate the influence of different illumination, and the discrete cosine transform is used to compress the extracted feature data. Finally, we take these extracted features as our training set and test set of the Bayesian network face classifier to train the network parameters and face recognition [1-4].

In order to find the relationship between facial features. It is desirable to consider that certain characteristics are caused by the same origin. For example, the eigenvectors of two eyes are consistent. It is very likely that these two observations are caused by the same hidden variable. At least, we can think that these characteristics are not completely independent. In the same way, we believe that at a more global level, all the visual features extracted from the same person face image determine the same identity. The model can be explained as follows: the above root node generation (node F) is composed of the relationship between the eyebrows (node B), the eye (node E), the nose (node N) and the mouth (node M). Therefore, this variable is used to simulate the correlation between different face regions. Variable F generates specific facial features (such as small nose or wide lips), which is represented as a second level node. Finally, these facial features produce consistent visual features. Note that our model introduces the relationship between observations: if nodes are observed, information about nodes can be deduced through nodes. On the contrary, it can be clearly seen that this model uses implicit variables to generate correlations between features.
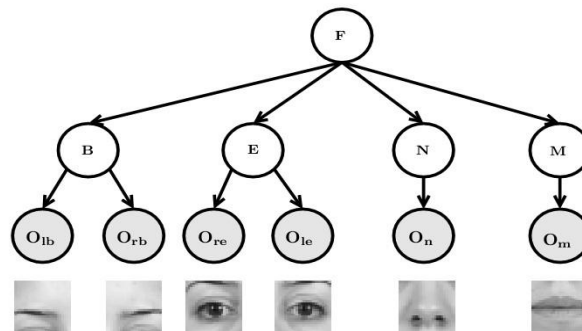

Figure.1 the model of face recognition algorithm based on Bayesian network

In the above models, the hidden nodes take discrete values, and the visual nodes take the multivariate Gauss function. In this way, the probability distribution of the first and second level nodes can be derived from probability tables. However, the node correlation distribution is Gaussian conditional distribution [5-9]

$$P(O = o \mid Pa(o) = i) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_i|^{\frac{1}{2}}} \exp\left(-\frac{1}{2}(o - \mu_i)^T \Sigma_i^{-1}(o - \mu_i)\right) \qquad (1)$$

Of these, $O = o$ is a case of visual features, and $Pa(o)$ i refers to the value of i of the parent node. N is the dimension that represents the eigenvector. That is the dimension of the feature blocks we have chosen. The μ_i is the mean and the Σ_i is the covariance of the Gauss condition distribution. The parameter of the Bayesian network is θ which is determined by the entire probability table and the mean value μ_i, and the Gauss conditional distribution variance Σ_i.

The local two element mode (LBP) is a texture extraction operator. The rule of LBP coding is to compare the pixel values of the 3 * 3 neighborhood position of a pixel to the central pixel value, if the value is greater than the central value, then it is set to L, otherwise the location is set to 0. The 0 and 1 are then composed of a binary code in a cis time sequence, and then the binary code is converted into a decimal value, which is encoded as the LBP of the central pixel. Since the binary encoding has 8 bits, LBP coding has a total of 256 different integer values with a maximum of 0 to 255. LBP can be used to make a rough location of the face.

Active Shape Model (ASM) is an image search method based on statistical models. The idea is to construct a variable shape template with different images. During the period, an energy function is defined, and the energy function is minimized by adjusting the model parameters, and the parameters of the minimum energy are selected as the model parameters. By adding a penalty factor to the parameter, the initial shape is constantly adjusted to match the desired shape. Compared with the active contour model, the advantage of ASM is that the parameters can be adjusted constantly according to the training sample, thus the change of shape is limited in a reasonable range.

In ASM, a set of feature points that can reflect face contour is used to represent face shape, and this set of feature points is called the point distribution model. When the feature points are selected, the point which can fully express the face contour is selected as the feature point, so that the point distribution model can describe the shape of the face very well. At the same time, these points should not only express the external contour of the face image well, but also express the outline of the internal organs very well. As shown in Figure 3.6, the point selected at the corner point in the face image is generally selected; the point at the T - shaped connection is selected; the point located on the face contour and located on the front of the two feature points on the front is the feature point.

2. Experimental results

In order to test the recognition performance of multi pose face, two groups of experiments were carried out. The XM2VTS database pays special attention to multi-mode authentication. The data topics include synchronous video and voice, including 295 human face images and audio and video segments at 4 different time periods. At each time period, each person was recorded 2 head rotation video clips and 6 voice segments. Since data acquisition takes a long time, significant variations in the customer's appearance, such as hairstyles, changes in face hair, the shape of glasses, and wearing glasses, are presented in the record.

In the first group, only 40 face images are selected as the training samples. In addition, 5 face images, except the front face, are selected from each type of face, and a total of 40 x 5=200 face images are used as test samples to carry out face recognition experiments, as shown in Figure 2.

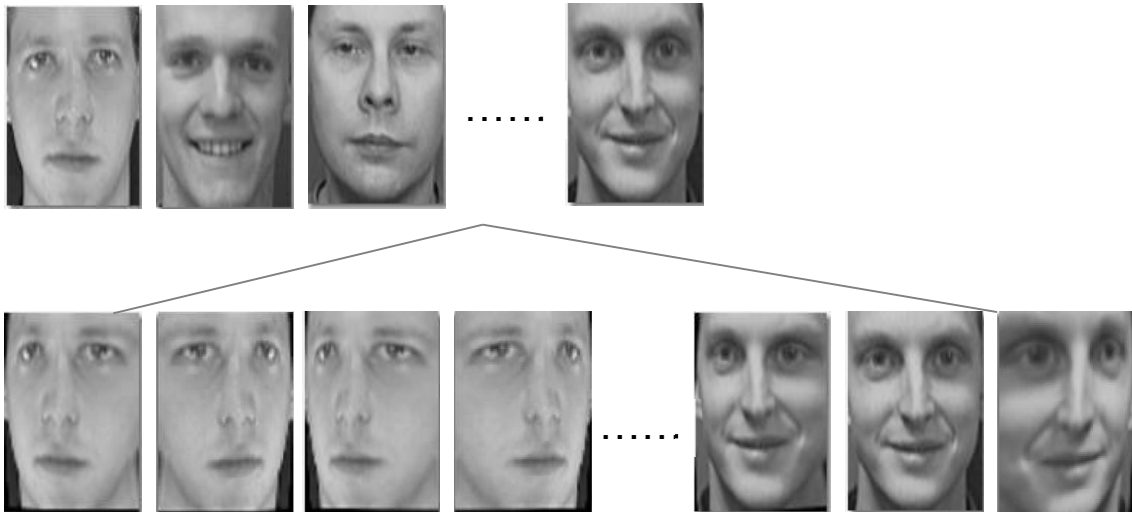Training samples (40):

Test sample (40*5=200):

Figure 2 The first group of multi-pose faces recognition experiments

Training samples (40+40*4=200):

Test sample (40*5=200)

Figure 3 the second group of multi-pose faces recognition experiments

Using the local weighted average face generation algorithm proposed in this paper, 4 face images of 15 degrees, 30 degrees and right 15, 30 degrees are generated respectively, and a multi pose face image database is formed with the frontal face images, and a total of 40 classes of 40 * (1+4) =200 face images are used as training samples, and the same test as the first group is used. Test set, as shown in Figure 3 The aim is to facilitate comparison with the first set of experimental results. In these two groups of experiments, 20 dimensional principal components of face images are extracted to form facial feature vectors for training and recognition. The experimental results show that the average face recognition rate of the first group is 43.5%, the average face recognition rate of the second groups is 65.9%, that is, the multi pose face recognition rate using this algorithm is 16.9% higher than the face recognition rate only based on the frontal face.

3. Conclusion and Prospect

This method effectively overcomes the problem of rapidly decreasing the recognition rate caused by multi pose face images and pose changes in multi pose face recognition. The experimental results show that the multi pose face generated by this algorithm can keep the local characteristics of the face very well, and have high similarity with the face in the XM2VTS database, and can effectively improve the recognition rate of the multi pose face.

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