Facial Image Prediction Using Exemplar-based Algorithm and Non-negative Matrix Factorization

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***Abstract*—Human aging face prediction is a popular research topic because of its various useful applications such as security system, missing persons search system, etc. In this study, we propose Exemplar-based Algorithm whose property considers the environment of human growth. Moreover, both the non-negative matrix factorization and linear interpolation methods are used to perform the prediction for six facial ROIs. In the proposed method, we employ the family images, in which each family member has more than one images at different ages. And we predict the image ROIs to replace the original ones to obtain the prediction result. However, it is difficult to collect the facial image ROI of families at various age, we also refer the databases from the internet. In experimental results, the correlation coefficient between the real and predicted images can reach 0.82. However, the factor such as expression and light in the reference images could result in lower correlation coefficient.**

I. INTRODUCTION

Human face prediction has many kinds of application such as finding a person who was missing for a long time, simulating the result of face change in medicine, etc. Currently research of human face prediction includes: Choi [1] used Principal Component Analysis (PCA) and 3-D Shape Model to capture the factor of aging change in face images and exploited the factor to put in predicted image, Lanitis and Taylor [2] proposed the recognition system of age change in human faces. They established the model of age function to be independent of age change. Other studies in [3-9] proposed different method to achieve prediction. In this paper, we propose a method, which utilizes the exemplar-based and non-negative matrix factorization (NMF) [10] schemes to predict the human aging face images.

In this study, we mainly use six features parts as the regions of interact (ROIs) which include left brow, right brow, left eye, right eye, nose, and mouth in a facial image to estimate the growing results. We also use the databases, which contain the family and non-family members' facial ROIs images at various ages in our experiments. The requirements of an valid image database are described below. First, the images must have corresponding age information. Second, the database is composed of aging facial images of many persons. Among the database, each person has image sequence at different ages. Third, there must be kinship between each family person. Finally, each image must be belonged to one family. The requirements mentioned above make data collection difficult. Therefore, we used the non-family people images sometime. Currently, many human face databases in the internet are open for public. For example, FG-NET aging database [11]. Although, GF-NET database provides numerous face images, it does not offer the facial image sequence of different ages of the persons in the same family

II. THE PROPOSED METHOD

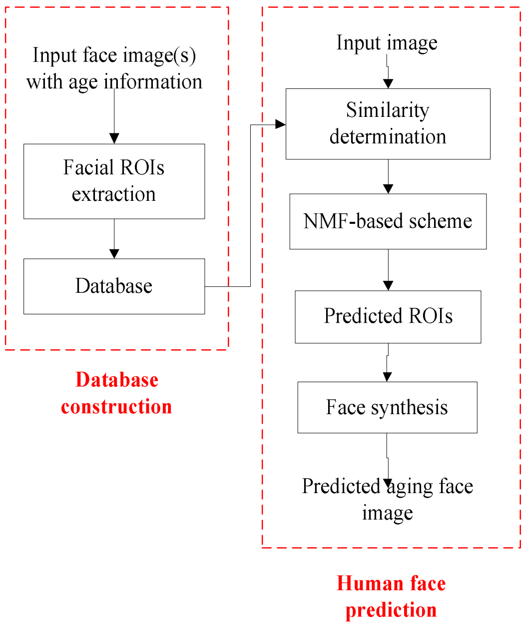

Fig. 1: The block diagram of the proposed method.

Figure 1 shows the block diagram of the proposed method, which contain two parts: the first part is database construction and the second is the prediction of human aging face image sequence. In the first part, we generate the database by extracting 6 ROIs in each face image. The database contents include: the location of ROIs, age, the family name, and kinship with family. In the second part, we compare the similarity between each ROI in the database and segmented ROIs in the input images. After obtaining the most similar ROI in the database, we employ NMF to determine the basis images W and weight factor matrix H. And we use the method of linear interpolation with H matrix to predict the sequence of ROI growth. Finally by synthesizing these sequences of six ROIs at each age into the facial model, we can obtain the predicted image.

II-1. RESEARCH METHOD

In this section, three methods related to this study are introduced as follows: Exemplar-based, feature parts capture, and NMF methods.

A. Exemplar-based Method

The Exemplar-based method has been successfully used in human face prediction [6] which supposed the 'A' conditions such as environment, physiology and psychology in growth was same as 'B' conditions, when A is similar to B in childhood. In this research, the Exemplar-based method is used between target image and referenced images in six ROIs. In order to obtain the results based on genetics, we use the family images as referenced images.

B. Feature Parts Capture

First of all, the six ROIs are captured in the source image shown in Fig. 2(a) by using Sobel edge detection in the horizontal direction. Equation (1) is used to find the horizontal edges in an image. Second, a threshold value is used to obtain a binary image shown in Fig 2(b). Third, by scanning the whole image, we can determine the position, length, and width of the six ROIs. Finally, the system put these data into the database automatically. This method can be faster than method in Ref. [12], because this method does not need to calculate and then analyze the histogram. However, the image quality must be improved by performing the noise filtering.

$$\mathrm{F}(x,y)=\mathrm{F}(x-1,y-1)+2\times\mathrm{F}(x,y-1)+\mathrm{F}(x+1,y-1)+(-1)\times\mathrm{F}(x-1,y+1)+(-2)\times\mathrm{F}(x,y+1)+(-1)\times\mathrm{F}(x+1,y+1) \quad (1)$$

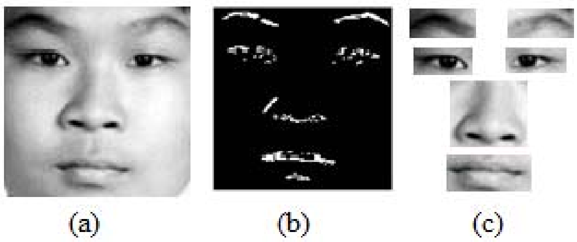

Fig. 2 The step of feature parts capture. (a) The source image. (b) The result of Sobel Edge Detection and binarization. (c) The result of feature parts capture.

C. Non-negative Matrix factorization (NMF)

The property of NMF is that the coefficients in both matrices W and H must be non-negative. The advantages of NMF are easy to understand and conformed to operational property of neural network. Lee and Seung [13] have successfully used the NMF method on human face analysis. In this study, we use the NMF technique to identify the hidden characteristic of ROI image of family members and then to predict the human face sequence in the growth.

The proposed algorithm using NMF is described as follows: First, according to the constructed ROI database, each **V** matrix is with the dimension $n\times m$. Second, setting the parameter r for the **W** and **H** matrices with the dimensions n×r and $r\times m$, respectively. The product of W matrix and **H** matrix is approximately **V** matrix. Equation (2) describes the approximately matrix operation in NMF.

$$\mathbf{V}nm \approx (\mathbf{W}\times\mathbf{H})nm = \sum_{a=1}^{r}\mathbf{W}na\times\mathbf{H}am \quad (2)$$

In (2), each **V** matrix is composed of the ROI image and the most similar ROI image sequence. The parameter n is the amount of information of each ROI image. The parameter m is the amount of ROI images. The parameter r is set using the constraint $(n+m)r<nm$. The **W** matrix is composed by the basise of wanted ROI image and the most similar ROI image sequence. Here **H** denotes the weighting matrix of W matrix corresponding to the V matrix.

In the NMF initialization stage, all the elements in both the matrices **W** and **H** are non-negative. The second step is the normalization of column elements of **W** matrix (the sum of the elements of each column is 1.0) and this is shown in (4). In the third step, the **W** and **H** matrices are iteratively modified according to (3)-(5), respectively. The **W** matrix is normalized in each iteration according to (4) until the mean squared error (MSE) between the original and iteratively generated **V** matrices, in which the later one is the product of **W** and H matrices unchanged or is equal to zero.

$$\mathrm{W}_{ia}^{new}=\mathrm{W}_{ia}\sum_{u=1}^{m}\frac{\mathrm{V}_{iu}}{(\mathrm{WH})_{iu}}\mathrm{H}_{au} \quad (3)$$

$$\mathrm{W}_{ia}^{new}=\frac{\mathrm{W}_{ia}}{\sum_{j}^{n}\mathrm{W}_{ja}} \quad (4)$$

$$\mathrm{H}_{au}^{new}=\sum_{u=1}^{m}\mathrm{W}_{ia}\frac{\mathrm{V}_{iu}}{(\mathrm{WH})_{iu}} \quad (5)$$

The fourth step is using linear interpolation on the **H** matrix which finished the iteration to predict the each weight of age calculated in (6).

$$\mathbf{H}_n=\mathbf{H}_1+\frac{\mathrm{H}_m-\mathrm{H}_1}{m-1}\times(n-1),\qquad 1<n<m \quad (6)$$

In (6), the parameter **H**n is the n-th interpolation weight and the **H**m is final weight. Each weight multiply the corresponding basis ROI image to construct the sequence of ROIs in growth calculated in (7).

$$\mathbf{V}_a=\mathbf{W}_1\times\mathbf{H}_{1a}+\mathbf{W}_2\times\mathbf{H}_{2a}+\cdots+\mathbf{W}_r\times\mathbf{H}_{ra} \quad (7)$$

In (7), the parameter **V**a is a-th sample. In this research, the quantity of **V**a is determined by the difference age calculated by the largest age of similar ROI image in the database subtract the age of wanted ROI image. Because we wanted to get the predictive sequence in each age, the difference age must subtracted one after above-mentioned calculation.

III. EXPERIMENTAL RESULTS

In this research, we used Visual C++ and Microsoft office Access to implement the proposed methods. Figure 3 shows the target image with twelve years old. Figure 4 shows the reference images which were the sequence image of father in growth. Figure5 shows the sequence image of mother in growth. The experimental result was divided into three parts: the basis image, the sequence of weight interpolation images, and the sequence of ROIs synthesis.

Fig. 3 The target image in 12 years old.

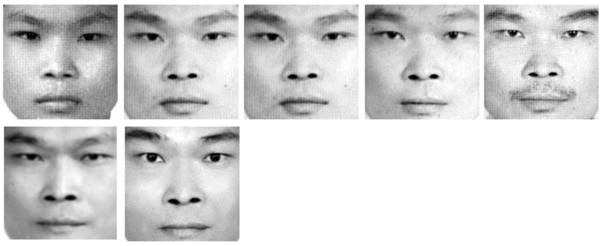

Fig. 4 The father's sequential images of 15, 18, 20, 30, 35, 45 and 50 years old.

Fig. 5 The mother's sequential images of 20, 30, 35, 40 and 45 years old.

A. Basis image

Figure 6 shows the ROIs basis image of reference sequence of father.

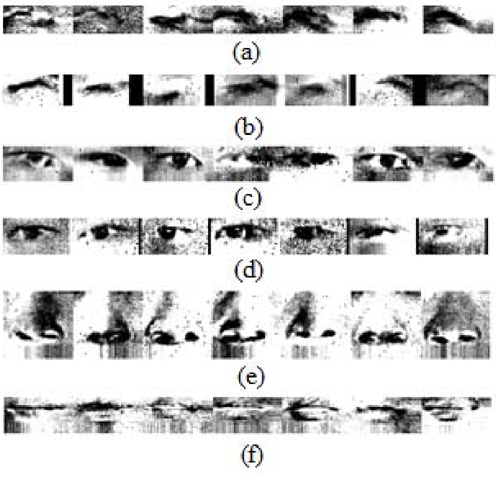

Fig. 6 The father's six ROIs basis image: (a) left brow. (b) right brow. (c) left eye. (d) nose. (e) mouth.

Because the feature parts were captured automatically, the ROIs image size was flexible in each image. In order to get the fix size of ROIs image sequence, we selected the largest length and width in the database as the standard. Figure 6(b) and 6(d) show the influence of escape scope (the black straight strip).

B. Sequence of weight interpolation images

While completing the weight linear interpolation, the ROIs image was recovered form **V** matrixes. And each ROI image represent a different age. Figure 7 shows the generated ROIs of six facial parts from 12 to 50 years old.

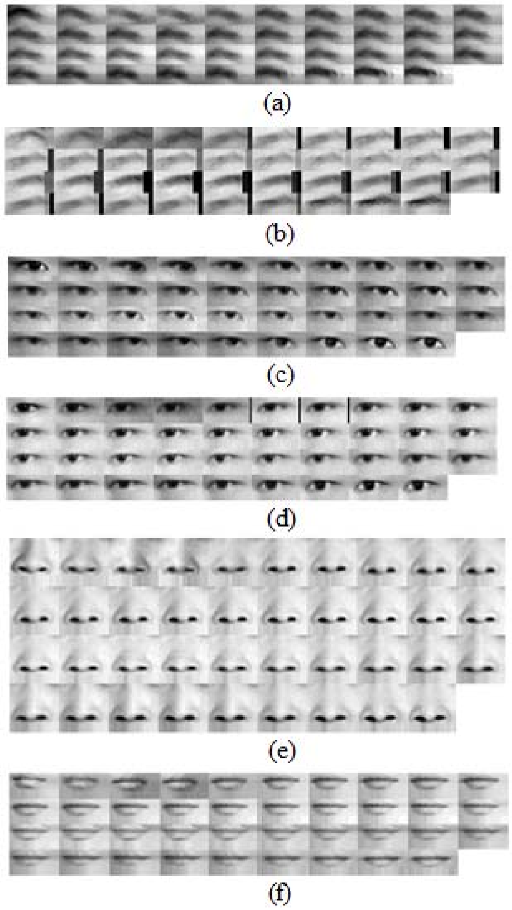

Fig. 7 The six ROIs image completed the weight linear interpolation in 12 to 50 years old. (a) left brow. (b) right brow. (c) left eye. (d) nose. (e) mouth.

Figure 7(b) shows that the black straight strip is affected by the basis image shown in Fig. 6(b). But this situation does not affect the result of face prediction. The black straight strip will not be used in synthesizing the final facial image.

C. Image synthesis

Image synthesis was used the original positions, length and width of each ROI of target image to synthesize each ROI image which we predict. Figure 8 shows the real image in 12, 15, 18, 21 and 23 years old. Figure 9 shows the image which completed the synthesis at the 12 to 50 years old.

Fig. 8 The real image in 12, 15, 18, 21 and 23 years old.

Fig. 9 The image completed the synthesis in the 12 to 50 years old.

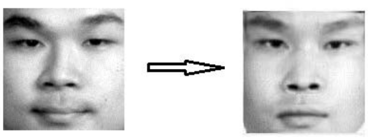

Fig. 10 The correlation coefficient between the real and predicted image is 0.82 in 18 years old.

Because each image has different luminance and angle, the synthesis images have gap of pixel value in the junction of synthesis. It can be removed in many ways, we use the business software to remove it. Figure 10 shows the gap removed image, and the correlation coefficient between the real and predicted image is 0.82.

IV. CONCLUSION

Both exemplar-based and non-negative matrix factorization are used in this research to predict the human face sequence. We predict six feature parts to instead of whole face to obtain more feasibility than that one. But the drawback is need numerous information of family images which is corresponded the conditions described before. The result in this study shows the variability and accuracy in better photo quality. The future work includes: (1) improve the similarity comparison between the ROIs in the target facial image. (2) consider furthermore the changes in face shape and wrinkle due to the aging effects.

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