A Novel Method for Computer Aided Plastic Surgery Prediction

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***Abstract*—In this paper, a novel method based on former cases for plastic surgery prediction is presented. This method takes a pre-operative frontal facial picture as an input. Landmarks of the face are then extracted and constitute a distance vector. As a set of facial parameters, such a vector is entered into either a support vector regression (SVR) predictor or a k-nearest neighbor (KNN) predictor which is trained on a set of pre- and post-operative facial distance vectors of former cases. After the predicted distance vector generated, new landmarks positions are updated and the final result is generated in terms of changes between predicted landmarks and the original ones. Several experiments are carried out and the results show a great accuracy of prediction, which proves that this method is of high validity.**

Keywords-ASM; SVR; KNN; plastic surgery prediction

I. INTRODUCTION

Human face plays an important role in daily life. With people's increasing pursuit of beauty and improvement of surgical techniques, plastic surgery has been more and more popular in recent years. Different from operations which mainly focus on the process and the ultimate recovery of patients, plastic surgery puts a high value on the post-operative appearances which patients care more about for their great significance.

Unfortunately, it is inconvenient and inefficient to make physician-patient communication about issues of the surgery and to perform a surgical planning just based on an imaginary post-operative outcome or a simple sketch. Therefore, there is a strong need for a method to provide intuitive results after the operation by both surgeons and patients.

A. Related Works

Some surgery simulation researches have been carried out in recent years, most of which employed a deformation model like mass spring model or finite element model to simulate soft tissue between skull and skin and calculate facial deformities after craniofacial surgeries. A study by Keeve et al. [1] in 1996 presented a system using finite element model and linear formulation to simulate the operation result. Koch et al. [2] in 1996 designed a prototype system to predict facial appearances after craniofacial and maxillofacial surgeries using finite element model constructed from facial data set. Koch et al. [3] made a further research in 2002, which extended to volumetric physics based on the approach in [2] and added validation and error analysis. However, the anatomy of face is too complicated to design an appropriate model and find right parameters for it. Additionally, it is troublesome for doctors to try time after time to simulate the wanted operation on a skull model.

Other researches with regard to facial beauty have also been performed. Tommer Leyvand et al. [4] in 2008 proposed a facial beautification method to generate a more beautiful face ground on a score provided by a beauty function. It is not suitable for plastic surgery prediction since almost all parts of the face are changed, which cannot be realized in reality.

B. Our Contribution

In this paper, a novel method is presented for post plastic surgery prediction based on accumulated former cases in the hospital which were not considered by the related researches above. The features of pre- and post-operative faces are treated as training examples for both support vector regression (SVR) predictor and k-nearest neighbor (KNN) predictor then a post-operative face is predicted with a new patient's pre-operative face entered.

The rest of the paper is organized as follows. Section 2 provides the methods employed to predict post-operative appearance of patients' faces. Section 3 focuses on the experiments

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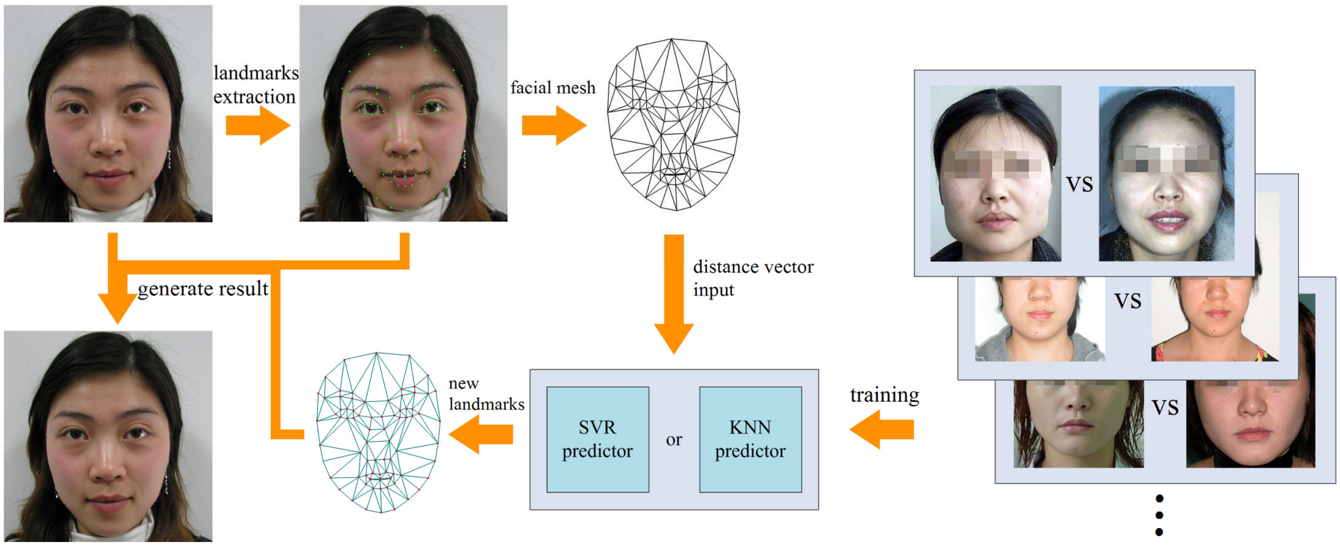


Figure 1. Process of plastic surgery prediction.

and the discussion about the methods and experiment results. Section 4 presents a conclusion and future work.

II. Methods

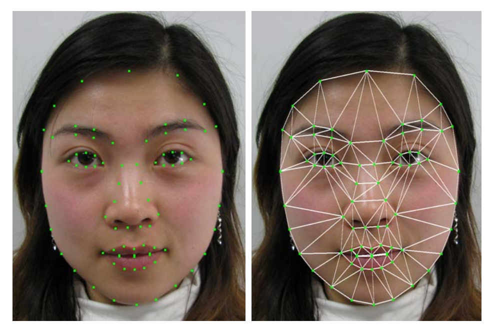
The process of our method is depicted in Fig. 1. A frontal facial picture is input and landmarks like corners of the eye, corners of mouth, points on face boundary etc. are extracted. These points are connected to generate a triangular mesh whose edges are stored in a distance vector as parameters of the face. The vector is input into the predictor using either SVR or KNN and the predicted vector is output. After that, new positions of the landmarks corresponding to the predicted vector are obtained. The visualized result is finally generated applying image morphing.

A. Feature Points Extraction

In this module, Active Shape Model (ASM) proposed by Cootes et al. [5] is applied to locate feature points of a face automatically such as corner points and boundary points of facial organs. ASM uses a Point Distribution Model (PDM) constructed from a set of correctly marked training images and a set of grey gradient distribution models, which describe local texture of each landmark point. This method represents a set of face feature points as their mean positions and a set of modes of variation which differ face by face. It will be more accurate if the new tested face is similar with one in the training set. So a large number of training examples are recommended to build the model.

In our work, 136 sets of face feature points, which contain 80 points each, are trained to build the ASM. The distribution of these feature points is illustrated in Fig. 2(a). Up to 22 points are located on the boundary of face because we pay more attention to the change of facial contour after a plastic surgery.

After the extraction of feature points, a Delaunay 2D triangulation [6] is performed to generate a triangular mesh covering the face as illustrated in Fig. 2(b). The mesh contains 215 edges in all. The lengths of 215 edges are stored in a distance vector $(e_{0,1},\dots e_{0,79},e_{1,2},\dots e_{78,79})$ as parameters of the face, where $e_{i,j}$ $(i<j)$ stands for the edge between point i and point j. Different order of elements in distance vector has no effect on the result but all vectors must be in the same order.



(a) (b)

Figure 2. Facial landmarks and mesh.

(a) 80 facial landmarks; (b) A Delaunay 2D triangulation mesh.

B. SVR Predictor

By comparing the pre- with post-operative face vectors, it is found that the differences are noticeable near the operative site while others are quite slight. For example, the bilateral facial contours between eyes and chin change largely while other parts like forehead, eyes, nose far from the Mandibular angle keep unchanged after the mandible reduction surgery.

In our work, the largely changed points are selected for different plastic surgeries. The post-operative distances between these points and the previously generated distance vectors are used to construct several SVR models to predict the corresponding distances of a new instance. Taking the mandible reduction surgery as an example again, 10 points are picked out

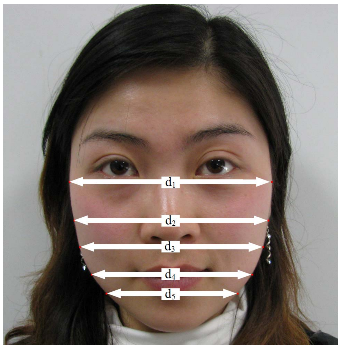


Figure 3. Target distance d_1~d_5 for SVR predictor.

and 5 SVR models are built to predict post-operative distances d_1~d_5 respectively, as shown in Fig. 3.

Given a training set $\{(x_1, y_1), ..., (x_l, y_l)\}$ where $x_i \in R^n$ (n=215 in our work) is an input and $y_i \in R^1$ is a target value, the SVR is to solve the following optimization problem [7]:

$$\min \frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) + \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) - \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \quad (1)$$

$$\text{subject to } \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0, 0 \le \alpha_i, \alpha_i^* \le C,$$

where α_i, α_i^* are Lagrange multipliers; $K(x_i, x_j)$ is the kernel function; ε is error tolerance; C is a constant greater than zero.

The SVR predictor is implemented using the libsvm library [8] and the Radial Basis Function (RBF) kernel

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \gamma > 0 \quad (2)$$

is chosen for the non-linearity of our problem. A grid search is performed to find a set of appropriate parameters to keep the mean squared error as low as possible.

C. KNN Predictor

An alternative method employed is the KNN predictor which is based on the thought that people with similar facial forms will have similar post-operative outcomes after the same plastic surgery.

The former cases containing several faces pairs are organized like a map. The i th element's key v_i denotes the distance vector of the i th face before surgery and the value of the element Δv_i denotes the corresponding change after surgery. v_i is normalized and Δv_i is calculated as

$$\Delta v_i = v_{ia} - v_i, \quad (3)$$

where v_{ia} scaled with v_i is the distance vector of the real post-operative face.

A new normalized instance v_{pre} is entered and compared with elements in the map to find the first K similar faces. The distance weight is calculated as

$$w_i = \frac{1}{\|v_{pre} - v_i\|}. \quad (4)$$

Then the post-operative distance vector v_{post} is predicted as

$$v_{post} = v_{pre} + \frac{\sum_{i=1}^{K} w_i \Delta v_i}{\sum_{i=1}^{K} w_i}. \quad (5)$$

However, in the process of prediction we found that the different facial expression of patients when taking pictures before and after surgery exerted a great influence on KNN search and the predicted result. Since we pay most attention to the surgeries which have an obvious effect on the facial contour, distances in v_{pre}, v_i and Δv on the facial contour are weighed more than ones in other regions which may be affected simply by a smile or blink.

The distance vectors are divided into m parts in order to eliminate the effect of expression and face painting with the weights distribution illustrated in Fig. 4 where different parts are assigned different colors and different weights. The distance weight is updated as

$$w_i = \left(\frac{1}{\sum_{l=1}^{m} \sum_{v_{pre}[j], v_i[j] \in \text{part } l} r_l (v_{pre}[j] - v_i[j])^2}\right)^{\frac{1}{2}}, \quad (6)$$

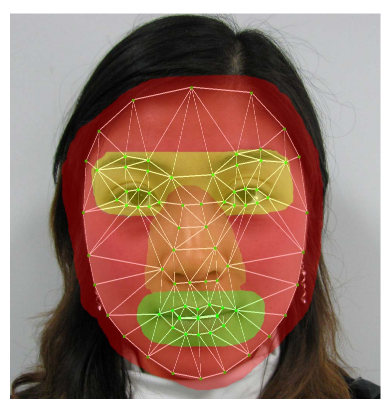


Figure 4. Weights distribution.

where r_l stands for the weight of part l in the KNN search. $v_{pre}[j]$ and $v_i[j]$ denote the j th element in v_{pre} and v_i respectively which lies inside this part. The prediction formula is updated as

$$v_{post} = v_{pre} + \frac{\sum_{i=1}^{K} w_i (s_1 \Delta v_i[1], \ldots s_l \Delta v_i[j], \ldots, s_m \Delta v_i[n])}{\sum_{i=1}^{K} w_i}, \quad (7)$$

where s_l stands for the weight of the part l and $\Delta v_i[j]$ stands for the j th element in Δv_i which lies inside this part. Although the number of parts divided is the same for both search and prediction, the weight r_l and s_l of each part are not necessarily equal.

D. Landmarks Update and Image Morphing

After getting the predicted distance vector v_{post}, the new positions of feature points should be updated based on it. We applied method presented in [4] to solve this problem. The Levenberg-Marquardt (LM) algorithm is used to minimize the problem [9] defined as

$$E(p_1, \ldots, p_n) = \sum_{e_{ij}} (\|p_i - p_j\|^2 - d_{ij}^2)^2, \qquad (8)$$

where $p_i(x_i, y_i)$ denotes the best updated position for feature point i. d_{ij} is the target distance in v_{post} corresponding to the edge e_{ij} between point i and point j. The solution of this problem is the changed landmarks corresponding to the predicted distance vector.

The visualized result is then needed to reflect the changes of the features points after the surgery. The multilevel free-form deformation (MFFD) [10] is applied to perform an image morphing based on the original feature points and the updated ones. This method consists of a set of free-form deformations which place increasingly refined control lattices on the image and adjust source features to target features step by step through the uniform cubic B-spline basis functions to generate a warp function. Through this function, a pre-operative facial picture is then converted into one which reveals the predicted result.

III. Experiments and Discussion

50 cases containing a frontal pre- and post-operative facial pictures are used for training both SVR predictor and KNN predictor. In our work, 10-fold cross validation is employed and the parameters for RBF kernel are obtained using a grid search tool. The leave-one-out test is used for validating KNN predictor. 10 different values of K from 1 to 10 are assigned to examine the mean squared error of the KNN predictor. The error is defined as the denominator of (6) simply replacing the

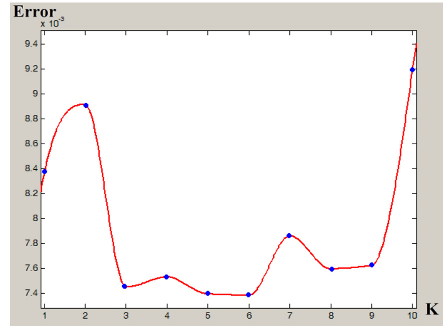
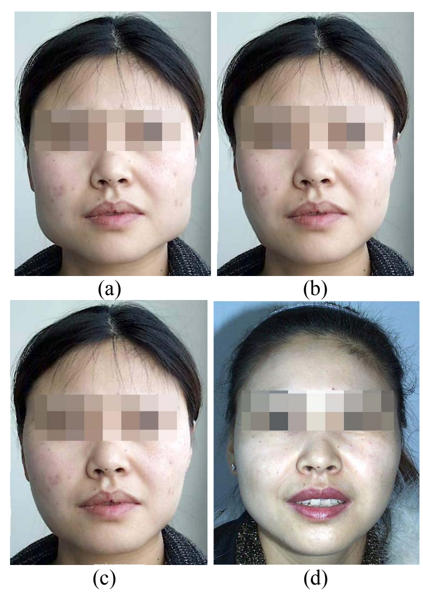


Figure 5. Prediction error with different K.

item $(v_{pre}[j] - v_i[j])^2$ with $(v_{ia}[j] - v_{post}[j])^2$ where v_{ia} and v_{post} are both normalized. 8 mandible reduction cases and 5 cheekbone reduction cases are tested and the mean error is illustrated in Fig. 5.

As shown in Fig. 5, the error begins to drop with K increasing and reaches the lowest point when K is between 5 and 6; then the error rises sharply with K larger than 9. It should be noted that the error in Fig. 5 does not provide as great significance as the value itself reveals because some subtle changes in parts like eyes will give people a quite different impression while large differences on other parts with a large error will be simply ignored by people. However, K = 5 is still chosen for our prediction for its best performance as the only benchmark.

The ASM model and prediction models are built beforehand. When a new facial image entered for prediction, these models need not to be rebuilt. In our experiments, either SVR or KNN prediction takes less than 10 seconds to produce the result. Fig. 6 shows the prediction of mandible reduction surge-



(a) (b) (c) (d)

Figure 6. Prediction result.

(a) Pre-operative face; (b) SVR predicted result; (c) KNN predicted result (K = 5); (d) Real post-operative result.

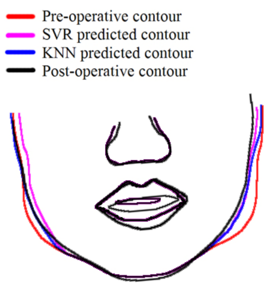


Figure 7. Contour comparison.

TABLE I. MAXIMUM/MEAN CLOSEST DISTANCE ERRORS.

Predictor	Error Measurements	
	Maximum (pixel)	***Mean (pixel)***
SVR	15.2643	7.05443
KNN	13.3417	6.31369

ry using both two predictors. The eyes of the patient are covered to protect her privacy. As shown in the figure, KNN predictor performs intuitively better than SVR predictor. To quantizing the comparison, facial contours are extracted as shown in Fig. 7 where different contours are assigned different colors and two error measures, Maximum Closest Distance and Mean Closest Distance, are applied. The former measure is defined as the max value of the set containing distances between points on predicted contour (purple line or blue line) and their closest neighbor on real post-operative contour (black line); the latter measure is defined as the mean value of the above set. As listed in Table 1, KNN predictor performs better than SVR predictor in the light of both criteria. The SVR predictor only changes distances between some points without considering changes in other parts even though the changes are quite slight. While KNN predictor synthesizes weighed changes of similar cases and the predicted result deviates less from the real post-operative outcome.

The prediction focuses on surgeries like mandible reduction and cheekbone reduction that obliviously change facial contour and put aside surgeries like double eyelid operation that produce only a small local change. The predicted results act as auxiliary means for doctors to make physician-patient communication about the issues of the surgeries and show patients intuitive outcomes after surgeries. It cannot provide doctors with exact details such as where to cut, how much to be cut etc. in real surgeries. The training and prediction is still limited to female because the number of cases for male is much smaller. Another limitation of this method is that only frontal pictures are used. Surgeries like augmentation rhinoplasty that have an apparent change on facial profile cannot be predicted using this method.

IV. CONCLUSION AND FUTURE WORK

In this paper, a novel approach for plastic surgery prediction is presented. Experiment results reveal that it is an effective method generating accurate outcome. The prediction based on lateral pictures is under development, which will be a complement to the current method. In addition, the method will be extended to 3D models and be used more effectively as an auxiliary tool for both doctors and patients in the future.

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