A STUDY OF QUANTIFYING FACIAL SYMMETRY USING HYPER-DIMENSIONAL COMPUTING TECHNIQUE

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Abstract - This study combines the characteristics of 3D facial contour images that can represent the 3D features of the overall face, and hyper-dimensional (HD) computing that can be used to calculate the similarity of the 3D contour images of the composite image of left and right faces (that is, the overall facial symmetry). We propose an assessment system of facial symmetry using HD computing technique for measuring the similarity of 3D facial contour composite lines.200images were recruited in a retrospective cohort study for building the assessment model of facial symmetry. 3D facial photos were captured by the Cone Beam Computed Tomography (CBCT) and 3D contour images were extracted from 3D facial images used for the feature images. We also developed a web-based system for clinicians to automatically assess facial symmetry based on our proposed HD computing technique. Additionally, or prospective study in clinical application, the proposed assessment model of facial symmetry using HD computing was applied for the automatic assessment of facial symmetry in 258 patients before and after or thognathic surgery (OGS). The experimental results revealed that the average accuracy of quantitative facical symmetry is 86% using HD computing model. For prospective study in clinical application, the average degree of improvement in facial symmetry after surgery was 26.7%.

I. INTRODUCTION

Three dimensional (3D) contour lines are similar to the Morie principle and contain the height distribution information of the 3D surface of an object, which can adequately represent the surface feature of an object in 3D space [42, 43]. The three-dimensional features of the whole surface can be adequately represented by converting the three-dimensional stereoscopic images into three-dimensional surface contours. In addition, Hyper dimensional (HD) Computing [44], a hyper-threaded alternative to current deep learning methods for processing sensory information based on boolean and numerical computation, is often used to encode and classify various kinds of data, mainly by converting images into real values in high-dimensional vectors and then manipulating these vectors. The main principle is to convert images into real values in high-dimensional vectors, and then manipulate these vectors for classification purposes. However, the basic definition of classification is that the higher the similarity is, the more it is clustered into the same category. Therefore, this project will extend the similarity calculation feature of hyper dimensional computing to use the similarity of the left and right facial contours of the 3D face as the quantitative estimation of the facial symmetry, and develop a "hyperdimensional computing-based machine learning model for quantifying the facial symmetry before and after orthognathic surgery," and then estimate the facial symmetry by subdividing the facial contours into regions. This will help clinicians to effectively diagnose the problem and plan orthognathic surgery to verify the effectiveness of pre- and post-operative facial symmetry improvement.

II. METHODS

A. Image pre-processing

3D image collection: 3D CBCT images, including 50 normal patients and 75 patients (each patient had a CBCT scan of the face before and at least six months after surgery), total 200 images.

Region of interest (ROI) of 3D facial surface extraction: After turning the head position according to the standard reference plane, we can get the 3D Region of Interest (ROI) image and remove the non-pigmented area (noise in the back and top area) (Figure 1).

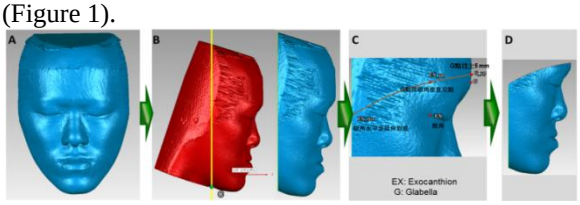


Figure 1.Region of interest (ROI) of 3D facial surface extraction.

Extraction and normalization of ROI contour image: The ROI is transformed into a three-dimensional contour line distribution and standardized in size, which is used as a source of feature images for quantifying the symmetry of the face in subsequent hyper dimensional calculations (Figure 2).

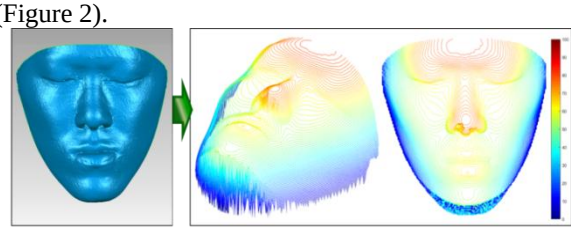


Figure 2.Extraction and normalization of ROI contour image.

The ROI extraction of left and right face: The left and right faces are divided according to the midline (the vertical line past the nasion point) to form the contour ROI images of the left and right faces respectively (Figure 3).

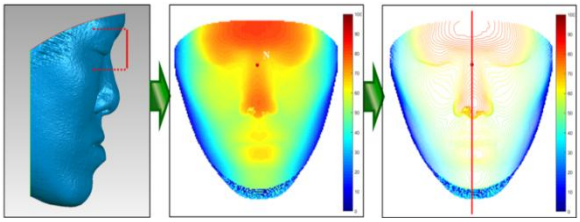


Figure 3.The ROI extraction of left and right face.

B. Labeling ground truth

Facial symmetry assessment by clinicians: The 3D facial images after head rotation are computerized and scored by a degree of facial symmetry questionnaire administered by a group of clinicians (plastic surgeons). The images are randomly sequenced, with only one image appearing on the screen at a time, and are presented in an auto-slide format (Figure 4). After five seconds of viewing each image, the image disappears, and the rater scores the image based on his or her impression of the image in the following three seconds. The 5-point Likert scale was used, with the most asymmetrical rating being 1 and the most symmetrical rating being 5; the raters would not be informed that duplicate images would appear during the rating. This rating has been performed twice, more than two weeks apart.

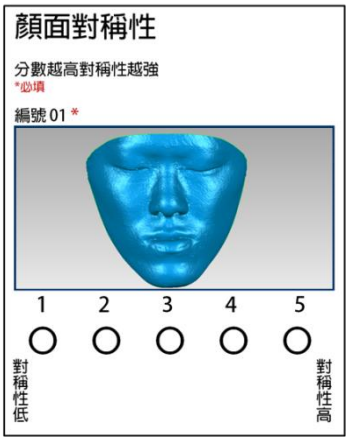


Figure 4.Facial symmetry assessment by clinicians.

Outlier removal: To avoid bias in questionnaire reliability analysis, outliers must be removed first. Two types of outliers have been defined: For rater outlier, in a two-week period, 50 samples were randomly selected to be scored again by all raters, and the intra class correlation coefficient (ICC) was used to test the internal reliability of the titers. The general criteria for interpreting ICC estimates are as follows: values less than 0.5, between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 indicate poor, moderate, good, and very good reliability, respectively. For scoreoutlier, after deleting the rater outlier and recalculating the mean for each sample, any score that deviates from the mean by more than three standard deviations (i.e., Mean±3SD) will also be deleted.

Ground truth calculation: After deleting the outlier of the symmetry score, all images are recalculated as the average of the symmetry score (SI_{truth}), which is the true value (ground truth) of the image's facial symmetry. The distribution of the average of each facial symmetry score (SI_{truth}) for all samples is shown in Figure 5.

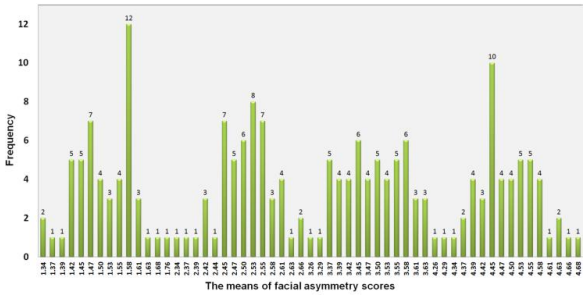


Figure 5.The distribution of the average of each facial symmetry score for all samples.

C. Creating the class division

For image classification (K-means), all images are classified into four categories (1~2, 2~3, 3~4, 4~5) according to the average of the symmetry score (SI_{truth}), which are used as the ground truth interval for each class of facial images (Table 1).

	Class 1 (N=50)	Class 2 (N=50)	Class 3 (N=51)	Class 4 (N=49)	Total (N=200)
Range	1.34~1.76	2.34~2.66	3.26~3.63	4.26~4.68	1.346~4.68
Mean±SD	1.51±0.08	2.51±0.07	3.49±0.08	4.48±0.09	2.98±01.12

Table 1.Means of facial a symmetry scores distributed per class.
N, number of samples; SD, standard deviation

D. Quantifying facial symmetry using hyper-dimensional computing technique

Using K-means automatically divides all samples into four groups: First, to calculate the similarity of the left and right face contour ROI images (facial symmetry) using HD computing for all facial images (1 - (Hamming distance)/Dimensions = SI_{HD}). Then, to divide all samples into four classes (clustering) using K-means algorithm as follows.

Step 1:
Setting the number of (K) classes to be divided into, for example: K = 4

Step 2:
K group centers are randomly given in the feature space (i.e., the symmetry of each left and right face contour ROI image) (to initialize each class center point).

Step 3:
For each data and all K classes, calculate the distance.
Step 4:
Each data is classified and awarded to the cluster that is closest to the cluster center.
Step 5:
For each class, the data is sorted and the new class center is updated with these data (i.e., the mean Means of the class is recalculated, i.e., the new class center).
Step 6:
The process from Step 3 to Step 5 is repeated until all the class centers do not change much (convergence) and stops.

Conversion of clustering results to facial symmetry values:

Normalization [0, 1]:
Assume that the result of the sample binning is the *Kth*class and its symmetry isSI_{HD}, the maximum value of the group is$Max_{HD}$and the minimum value is Min_{HD}.

The symmetry value after normalization is

$$SI_{HD_normalize} = (SI_{HD} - Min_{HD})/(Max_{HD} - Min_{HD})$$

For example: The sample falls in class 2,
$SI_{HD_normalize}$ = (0.9384 –0.9125) / (0.9518-0.9.125) = 0.659

Converting the normalized symmetry value into the absolute value of facial symmetry:
The K_{th} class's facial symmetry truth value (Ground truth) interval, the maximum value is Max_{truth}, the minimum value is $\text{Min}_{\text{truth}}$.

$$SI_{HD_absolute} = \text{Min}_{truth} + (\text{Max}_{truth} - \text{Min}_{truth}) \times SI_{HD_normalize}$$

For example: The sample falls in class 2,

$$SI_{HD_absolute} = 2.34 + (2.66 - 2.34) \times 0.659 = 2.551$$

Cross validated error: The training set is partitioned into K subsamples, a single subsample is kept as data for validating the model, and the other K - 1 samples are used for training. Cross-validation is repeated K times, once for each subsample. In this study, K = 5, that is 160 samples are randomly selected for training and 40 samples are used for testing, for a total of 5 iterations. For each round of testing, each test sample is given a HD computing result of the quantified face absolute symmetry value $SI_{HD_absolute}$. Finally, comparing $SI_{HD_absolute}$ with the true value SI_{truth} for calculation of the error rate $| SI_{truth} - SI_{HD_absolute} | \div SI_{truth}$.
Additionally, we developed a web-based system for clinicians to automatically assess facial symmetry based on our proposed HD computing technique. After logging in to the system, the user can query the facial symmetry score of a patient by using the patient's chart number and selecting the 3D facial image for assessment. The facial symmetry score is then displayed in the query results along with patient's 3D facial image (Figure 6).

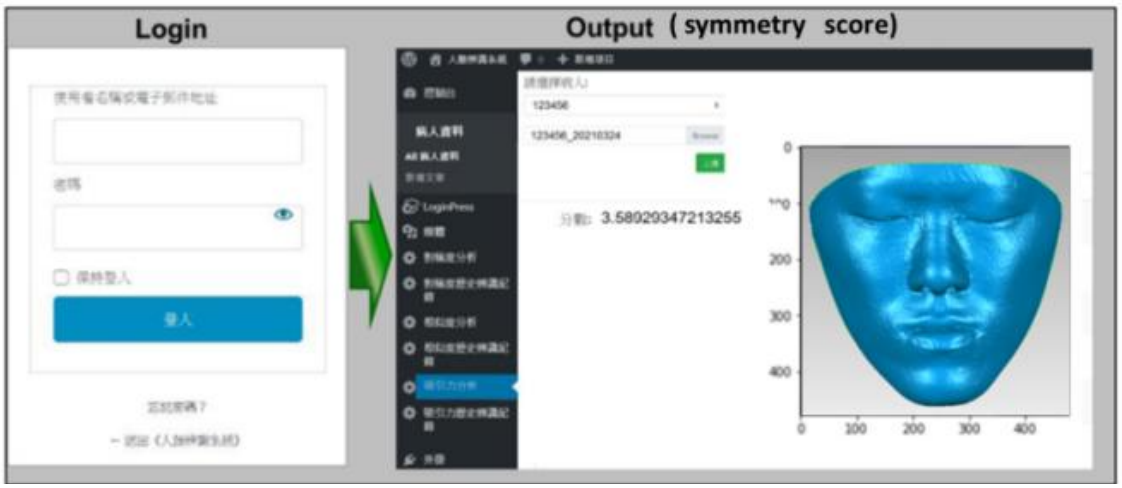


Figure 6.Web-based system for automatic facial symmetry assessment.

E. Automatic assessment of facial symmetry before and after orthognathic surgery (OGS)

For prospective study in clinical application, the proposed assessment model of facial symmetry using HD computing was applied for the automatic assessment of facial symmetry in 258 patients before and after orthognathic surgery (OGS). All participants were included if they were aged 20–30 years, were of Chinese ethnicity, had nocraniofacial anomalies, and had no history of facial trauma.

III. RESULTS

For building the assessment model in quantifying facial symmetry using HD computing technique, the average accuracy of quantitative facical symmetry is 86% using HD computing.

For assessment of facial symmetry before and after OGS, the preoperative scores of the patients ranged from 1.82 to 3.31 (mean = 2.51). In the post operative

evaluation, the facial symmetry scores of the patients ranged from 2.88 to 4.35 (mean = 3.75), constituting a significant improvement (p = .000). The average degree of improvement in facial symmetry after surgery was 26.7% (Table 2).

	Preoperative symmetry score	Postoperative symmetry score	Improvement (%)
Range	1.82~3.31	2.88~4.35	23%~95%
Mean±SD	2.51±0.37	3.75±0.43	35%±7%
p-value		0.000*	

Table 2.Facial symmetry assessment before and after OGS using the proposed HD computing model.
SD, standard deviation

IV. DISCUSSION

The present results revealed that the proposed HD computing model can be used by clinicians to obtain an objective facial symmetry score for a quantitative evaluation of improvements in surgical outcomes (Table 2). The web browser–based user interface enables clinicians to conduct effective and rapid assessment, thus contributing to effective doctor–patient communication and decision-making (Figure6). Clinicians must convey the treatment results to their patients in a transparent and objective manner, and the proposed machine learning model can help clinicians do so. However, the patient's subjective assessment may disagree with the score that is output by the model. Thus, clinicians should explain to the patient that the machine learning score is but a generic indicator. Nonetheless, we contend that machine learning results accord with how facial symmetry is generally perceived.

V. CONCLUSION

This work is the first attempt at automatic facial symmetry assessment before and after OGS surgery by using the HD computing model based on 3D facial images. This approach could be integrated into 3D surgical simulation in the near future to enable surgeons to plan treatments more effectively.

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