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A Deep Learning Approach for Predicting Subject-specific Human Skull Shape from Head toward a Decision Support System for Home-based Facial Rehabilitation

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Abstract - Prediction of human skull shape from head is a complex and challenging engineering task for the development of a home-based facial rehabilitation system. The present study aimed to develop a novel approach based on deep learning models to reconstruct the human skull shape from head. A head-to-skull generation workflow was developed and evaluated. A database of computed tomography images of 209 subjects was used. 3D head and skull geometries were reconstructed and then their respective descriptors (head/skull volumes, sampling feature points and point-to-center distances, head-skull thickness, Gaussian curvatures) were extracted. Traditional regression neural network and long-short term memory (LSTM) were implemented and evaluated. The mean error between the DL-predicted skull shapes and CT-based skull shapes ranges from 1.67 mm to 3.99 mm by using the regression deep learning model and the best learning configuration. The volume deviation between predicted skull shapes and CT-based skull shapes is smaller than 5%. The present study suggested that regression deep learning model allows human skull to be predicted from a given head with a good level of accuracy. This opens new avenues for the rapid generation of human skull shape from visual sensors (e.g. Microsoft Kinect) toward a computer-aided vision system for facial mimic rehabilitation.

Keywords: Deep learning, head-to-skull prediction, CT images, regression neural network, long-short term memory (LSTM) network.

I. INTRODUCTION

The estimation of external facial geometry from internal skull geometry was commonly performed in forensic facial reconstruction [1]. Thus, the relationship between facial features and parameters of the skull could be established.

Manual sculpturing could be used for this complex task. However, advanced anatomical knowledge and artistic modeling expertise are required [2]. Recently, automatic reconstruction with computer-aided system has been investigated to obtain consistent and objective outcomes [3]. Classical statistical methods have been usually used to learn this relationship to reconstruct parametric head model. However, the inverse relationship from head to skull is still misunderstood. Note that the bony structure like skull plays an important role in the dynamic movements (e.g. rotation) of the head and facial mimic expressions (e.g. smiling) toward a real-time and home-based facial rehabilitation system. The accurate reconstruction of a skull ensures a high level of accuracy for the definition of muscle insertion and attachment points, joint center location and contact surface estimation. Thus, a novel computational approach is needed to achieve this complex challenge.

Modern artificial intelligence (AI) techniques like deep learning have been recently developed to open new avenues for AI-based applications. In particular, new algorithms and model architectures have been proposed leading to successful applications in many fields such as image segmentation, object recognition, speech recognition, or robotics. Deep learning models range from a connection of dense layers to specific classes of architectures for image and signal data processing. In particular, convolutional neural network (CNN) model was developed by inspiring the visual cortex in animals to capture and process images. Recurrent neural network (RNN) was developed for time-series data. However, deep learning approach is still not applied to study the relationship between external head features and internal parameters of the skull. Consequently, this present study aimed to develop a deep

learning approach to reconstruct automatically the human skull shape from a head model. Two deep learning (e.g. regression neural network and LSTM) models were developed and evaluated.

II. METHODS

A. Skull shape generation workflow

A head-to-skull generation workflow was developed and shown in Figure 1. A database of head and skull was reconstructed using medical imaging, segmentation and 3D reconstruction methods. Then, head and skull features and descriptors were extracted from the reconstructed models. Two deep learning (regression neural network and long-short term memory (LSTM)) models were developed and evaluated using the extracted features and descriptors as their inputs. The system output was the subject-specific skull shape. The accuracy analysis was performed using a cross-validation process. Finally, the best and worst cases were reconstructed and analyzed.

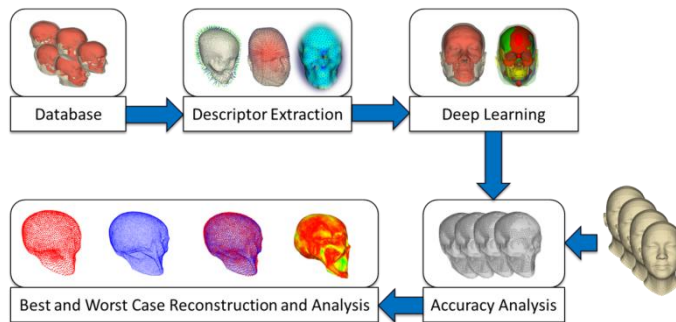


Figure 1. Overview of our skull shape generation workflow from head shape information

B. Database and feature engineering

The Cancer Imaging Archive (TCIA) database [4] was used in this study. This database includes the CT images of 298 patients. However, only 209 patients (160 males and 49 females, age ranging from 34 to 88 year olds) with full head and necks were included. A semi-automatic segmentation process was performed to extract and reconstruct 3D shapes of heads and skulls of 209 patients. A thresholding process was applied and then a manual post-processing was conducted for each CT dataset. Machine cube algorithm was applied to reconstruct the 3D geometries. These steps were conducted using 3D Slicer software. Finally, 3D geometries of head and skull were smoothed and post-processed using MeshLab software.

The first descriptor is the volume. Based on the covering shapes of the 3D reconstructed heads and skulls, their respective volumes and head-skull differential volumes were computed using available functions of the CGAL library [5].

Gaussian curvature descriptor was also computed for each pair of head and skull shapes using open source Libigl C++ library as the second descriptor. The third descriptor is the head-skull thickness. To compute this descriptor, each pair of head and skull shapes was resampled with the same number of sampling points. Sampling rays were defined from the global coordinate center and then moved to reach the covering shape of each pair of head and skull. Then, intersection points were extracted. Finally, the distance between each pair of head-skull feature points was computed and used as the head-skull thickness. The final descriptor is the distance from each feature point on covering shapes of head and skull to the original of the global coordinate system. Finally, all these distances were computed and saved for further processing.

C. Deep learning models

Two deep learning models were used and evaluated in this present study. The first model relates to a regression deep neural network. The second one deals with a long-short term memory (LSTM) network model. A hyperparameter tuning process was conducted to determine the optimal values for regression deep neural network and LSTM models.

The regression deep neural network includes several dense layers to describe and map the relationship between a set of independent variables X and a set of outputs Y . In this present study, the hyperparameter tuning was conducted to obtain an optimal set of hyperparameters including 5 hidden layers with 150 neurons for each layer, rectified linear unit (ReLU) function as activation function, and epochs and batch size of 1000 and 875 respectively.

The LSTM network is a recurrent neural network for solving the vanishing gradient problem. This deep learning model has specific gated structure to serve as memory to learn more efficiently the dependent relationship between input data set. Performed hyperparameter tuning was also conducted to determine the optimal set of hyperparameters (i.e. one hidden layer with 50 neurons, rectified linear unit (ReLU) and hard sigmoid functions as activation and recurrent activation functions and epochs and batch size of 100 and 875 respectively).

D. Accuracy analysis

A 10-fold cross-validation process was conducted. For each run, the database was divided into training (80%) and testing (20%) sets. The mean and root mean square errors were used for this accuracy analysis. A regression study on the variation of numbers of patients was also performed with a step size of 20 patients to determine the optimal number of patients needed

for our head-to-skull prediction problem. Note that the 10-fold cross-validation was repeated for each analysis. The root mean square error was used as evaluation metric. Based on the accuracy analysis, the best and worst predicted skull shapes were reconstructed and evaluated.

III. RESULTS

The mean error distribution of the regression deep neural network and long-short term memory model using the SD learning configuration from the 10-fold cross-validation process is shown in Figure 2. A better accuracy level was achieved with regression deep neural network model.

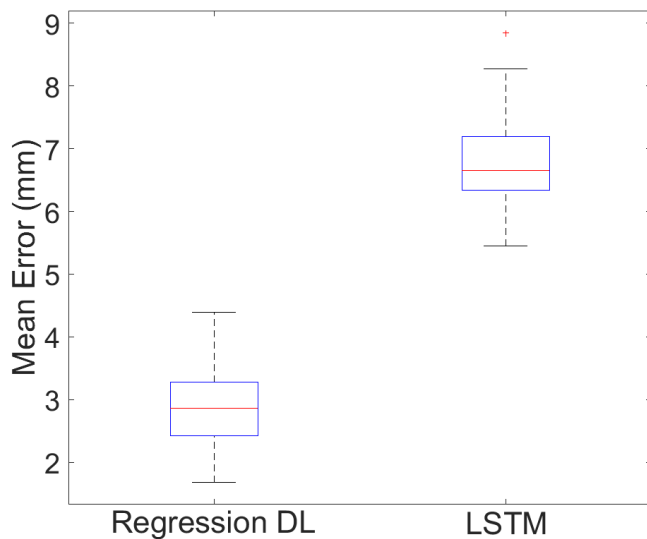


Figure 2. Mean error distribution of the regression deep neural network (DL) and long-short term memory models using SD learning configuration from the 10-fold cross-validation process.

The best and worst predicted skull shapes are shown in Figures 3 and 4 respectively. Regarding the worst case, the mean error between the AI-based skull and CT-based skull shape is around 3.99 mm. The mean and root mean square errors of the Hausdorff distance are 3.7 mm and 4.3 mm respectively. The maximal error is 15.6 mm. The volume deviation between predicted skull shapes and CT-based skull shapes is 104 cm³ (3.7%). Regarding the best prediction case, the mean error between the AI-based skull shape and CT-based skull shape is around 1.67 mm. The mean and root mean square errors of the Hausdorff distance are 2.5 mm and 3.1 mm respectively. The maximal error is 15.7 mm. The volume deviation between predicted skull and CT-based skull is 12 cm³ (0.5%).

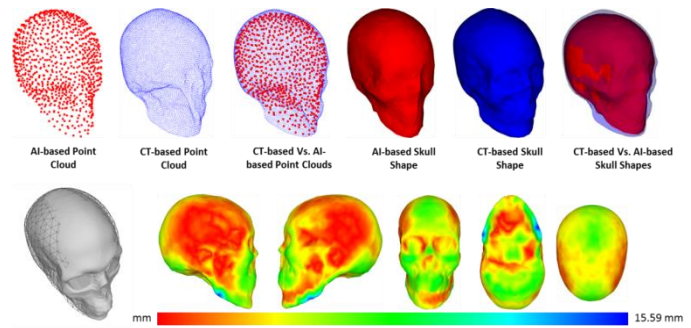


Figure 3. The worst predicted skull shape using regression deep learning model: upper part shows the comparison between AI-based predicted skull and CT-based skull shapes while bottom part shows the related Hausdorff distance deviation map.

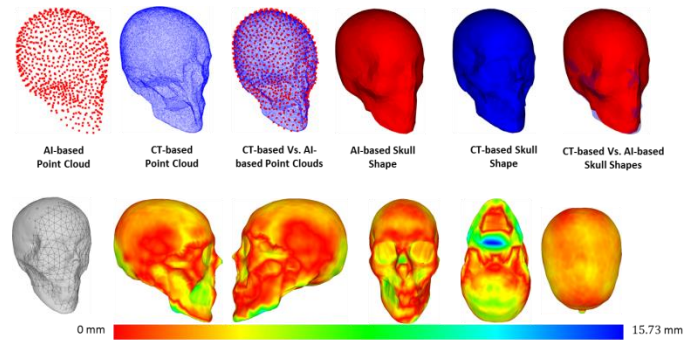


Figure 4. The best predicted skull shape using regression deep learning model: upper part shows the comparison between AI-based predicted skull and CT-based skull shapes while bottom part shows the related Hausdorff distance deviation map.

IV. DISCUSSION

Skull prediction from head surface information is a complex and challenging engineering task for the development of a computer-aided vision system for facial mimic analysis and rehabilitation. While skull-to-face prediction problem has been widely performed in forensic facial reconstruction [6-7], the head-to-skull prediction is still misunderstood. In this present study, this complex prediction problem was studied using deep learning models leading to a good level of accuracy (i.e. mean error ranges from 1.67 mm (1.14%) to 3.99 mm (2.72%)). Moreover, statistical shape modeling (SSM) has been widely studied in computational anatomy domain for automatic segmentation of biological organs like liver or lumbar spine. This approach was also used to describe the relationship between face and skull in our previous study [8]. However, small number of subjects was commonly used for statistical learning and inference. Moreover, the reconstruction accuracy is still not high with a relative error of around 10%. Generally speaking, while statistical methods aim to focus on the input and output relationships, deep learning methods focus on the prediction capacity to ensure good generalization ability with new data. This study suggested that regression deep learning

model coupled with some specific geometrical processing procedures allows human skull to be predicted from a head surface with a good level of accuracy. This opens new avenues for the rapid generation of human skull from visual sensors (e.g. Microsoft Kinect) toward a computer-aided vision system for facial mimic rehabilitation.

V. CONCLUSION AND PERSPECTIVES

A novel approach was proposed to predict human skull from head surface information. Obtained results suggested that regression deep learning model allows human skull to be predicted from a head surface with a high level of accuracy. This opens new avenues for the rapid generation of human skull from visual sensors (e.g. Microsoft Kinect) toward a computer-aided vision system for facial mimic rehabilitation. As perspectives, muscle network will be incorporated into the present workflow. Then, facial mimic movements will be tracked and animated for evaluating and optimizing the rehabilitation movements and exercises.

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