Extraction of Geometric Attributes Based on GAN for Anatomic Prosthesis Modeling

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***Abstract*— This research addresses the anatomic prosthesis modeling problem based on contour reconstruction from Computed Tomography images. The new neural network techniques permit predicting the geometric attributes of bone failures that cannot be obtained by symmetry. This paper presents a method based on Generative Adversarial Network (GAN) applied to build anatomic 3D geometric models of a skull prosthesis. The method performs the calculation of geometric descriptors as parameters to fit a curve on each Computed Tomography slice. These features can be estimated by the network who will be trained with a database of descriptors. The curve descriptors are formed by the fixed points around the edge that better represent a geometry, and a curve section can be described using the Cubic Splines method in order to complete the missing information on an open edge. The curve that fits a missing region to each CT slice can be superimposed to define the stack of images to build a 3D virtual CAD model. A prototype software system was implemented in Python in order to calculate the edge parameters and generate the computational model to printing. The results evaluate the similarity measured between the estimated and real coordinates and demonstrate the feasibility of the proposed method.**

I. INTRODUCTION

The digitization of objects allows us to evaluate and test its morphologic properties as a rigid body entity. Thus, in medicine, this digitization allows to get several information about a structure in order to predict diseases and plan operations. The standard file Digital Imaging and Communications in Medicine (DICOM) [1] allows exchange information for different platforms, and it contains in its inner protocol the images form computed tomography (CT).

In skull analysis we get access to 2D slices images from a DICOM file and we can handle each image separately and to build the corresponding 3D geometric visualization. This functionality able us to apply to geometric attributes extraction of skull bone,

In cases of bone failure, the slices of the skull have a missing region with congenital origin or caused by an accident or disease. Failures in the skull with bone missing regions can be remedied by a prosthesis. The investigation about shape repairing by image processing techniques is a feasible strategy to model creation for anatomically replace the missing bone in the skull.

In the present work, we apply A.I. (Artificial Intelligence) approach to look for the best solution for prosthesis modeling. We carry out a comparative analysis from knowing techniques and compare them with the proposed method, which is based on training a neural network with a database of flawless skulls for the repair of a flawed skull.

Due to the use of curve descriptors and slice-by-slice repair, the region of interest for the study will be the calvaria region, where we will prepare a database with 89 skulls without fracture and in each skull 30% of the descriptors will be removed.

According to skull anatomy described in [2], the calvaria region is formed by frontal bone, occipital bone and parietal bone. Fig.1 represents the calvaria region of the skull that will be considered to the reconstruction proposed method. The study was based in this region because the shape's characteristic is similar among C.T. slices, and then it is possible to get the respective curve descriptors without any extra pre-processing operation on the image.

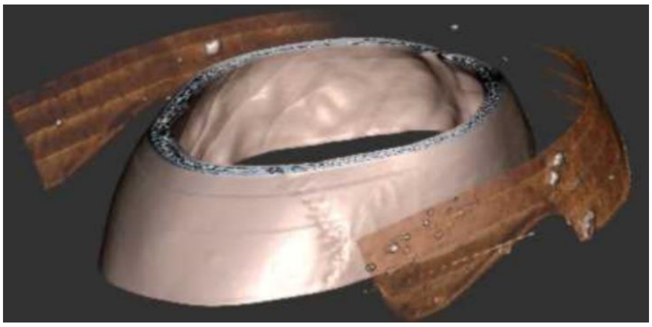


Figure 1. Calvaria region reconstructed from a human skull.

II. BACKGROUND

A bone failure regardless of its cause represents a structural failure in the skull making the affected region more vulnerable, in addition to the aesthetic factor that ends up causing discomfort to the individual.

Given the geometric complexity of the human skull, more advanced techniques are often required in order to create a personalized model for the patient. An anatomical prosthesis has the characteristic of correcting a specific failure because it is modeled precisely for this purpose. The digital repair of objects occurs in different ways depending on the desired time and quality, and for the modeling of prostheses, the main criterion is quality, which allows us to use techniques that demand more time. The difficulty in creating an anatomical prosthesis is the lack of information about the removed part. As we have no information about the missing part, what we have left is to estimate the missing part based on the part we have and previous knowledge of geometry, in some cases it will be necessary to have similar models to perform the reconstruction.

Techniques such as mirroring and searching for similar geometry are often used for bone's geometric modeling.

The mirroring technique uses the bilateral symmetry of the human skull to estimate the missing part on the other side, this technique has good results and is easy to implement, however it should only be used for lateral fractures since frontal fractures cannot be resolved by symmetry. Some initiatives to shape recovering from images was explored in [3] by using a PSO approach in order to find markers to represent the frontal bone curvature, therefore new A.I. based strategies were necessary to improve de results accuracy.

As presented in [4] the search technique consists of repairing slice by slice searching for the closest slice in a database, this technique has good results and can be used for frontal repair. However, as it is a direct search in database and maybe the found closest slice couldn't be good enough increasing the error among slices. This is due to the database without enough images causing the lack of skulls to similarity analysis to the one you want to rebuild.

For the solution of the problem we seek a middle ground between the result of mirror technique and search technique, we wish to have a good final aspect with the least possible error and that the technique works for the entire calvaria region. The proposed solution is based on [5] where a Generative Adversarial Neural network (GAN) was used for object repairing, whose network can generate images based on previous training.

The neural network applied in this research is presented in fig.2 as a modification of GAN by using linear regression instead of classification (RN), which allows to directly repair the skull failure. The RN network was trained with a batch size of 10, in 5 epochs and a mean squared error loss function. Just like the search solution we need a database that contains a good variation of skulls, thus making it possible to learn and predict lost parameters.

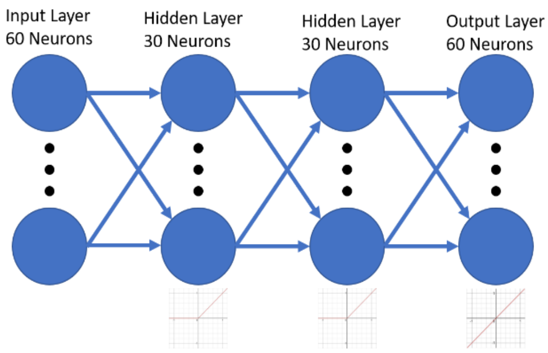


Figure 2. Proposed Network RN based in GAN.

III. MATERIALS

The dataset used is from the Center for Advanced Research in Imaging, Neurosciences and Genomics (CARING) [6] in the form of a non-commercial license. The dataset contains 491 skulls with and without fractures.

For the present study, 90 skulls without fractures were used being that 1 among them was chosen for the subsequent reconstruction testing. The number of skulls was limited in order to reduce the training and searching times.

The program was written in Python language using the IDE Spyder. Python was chosen due to the access of specific libraries to all computational tasks, as i) *PyDicom* for reading the DICOM file and extracting the TAGs, ii) *NumPy* for mathematical calculations, iii) *Pandas* for creating the database in CSV, iv) *SciPy* for image processing, v) *Python-STL* for creating the file in stl (to 3D printing), vi) *Keras* with *TensorFlow* for creating and training the neural network and finally vii) *Sklearn* for testing hyperparameters and cross-validation.

The computer used for the training has the following AMD Ryzen 5 3600X processor configuration, 32GB of RAM and a super RTX 2060 graphics card with 8GB of memory. The processing capacity affects only the training time, making it possible for the method to be used on any other equivalent machine.

The 3D Builder software was used to repair the imperfections of all parts in the model that could affect the print quality. The Blender software can also be used for the same purpose.

The model was printed using the Creality CR10 S 3D printer which uses fused material printing (FDM). The material used was polylactic acid (PLA) which is a plastic easily found for 3D printing [7]. As the model will be for viewing purposes only, for this research it does not need to be biocompatible. Once the geometric model validated, it is possible to apply the same method for any material or printer compatible with the STL file.

IV. METHODOLOGY

The preparation of the database involves the dataset of the region that you want to reconstruct. To our case, we selected a skull dataset without bone fractures from each DICOM file. After we applied image processing steps and performed the extraction of geometric attributes, we did the insertion of them in the database.

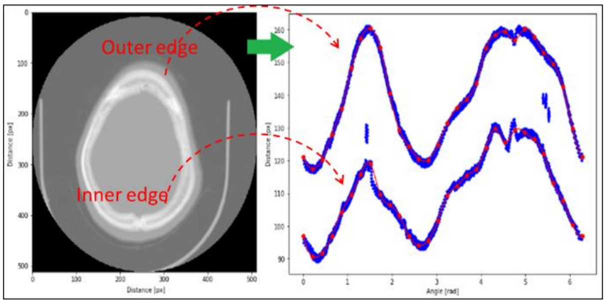
The image extraction was performed from DICOM by TAG Pixel Data (7fe0, 0010), in which the image is read as a matrix where each element represents the pixel intensity. The images are 512x512 pixels in size and intensity ranging from -2000Hu to 3000Hu [8]. These values refer to the Hounsfield scale in which the value -2000 represents the region outside the CT and the values from -1000 to 3000 the relative density of the material on the HU scale.

According to the Hounsfield scale, human bone ranges from 700 to 3000 HU, ranging from soft bones to hard bones, based on tests, the value of 1500 HU for skull bones was reached, this value was used as a criterion for image segmentation.

According to [9] the image was binarized after segmentation, assuming a value of 0 for the bone region, in addition, the region around the bone was cleared of any imperfections that would affect future steps.

The edge detection algorithm by the SOBEL method was used to enhance the skull contour and reduce the amount of information and smooth the curves. Using the signature, the image was transformed into a continuous curve where each pixel is now represented by its distance from the center of the image and the respective angle formed.

The image was then separated into an external curve and an internal curve, where points were equally spaced on the angle axis and their respective distance were obtained according to fig. 3.a original image in HU scale and in fig. 3.b the blue curve is the original curve, the red curve is Cubic Spline and red dots are fixed points (markers). From [10] the number of points was tested using the comparison of the original curve and the curve obtained by the Cubic Splines method with the testing points.



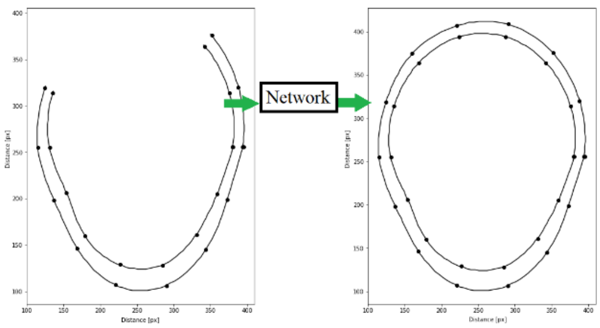
(a) (b)

Figure 3. (a) CT grayscale image. (b) Image after transformation.

The total amount of 30 points per curve were inserted into the database and based on the performed tests they proved to be enough. The image was reduced in scale average from 262,144 pixels (blue dots in figure 3.b) to 60 pixels (red dots in figure 3.b), which represents about 99.98% reduction in the amount of information needed to represent the skull slice.

The process was repeated for the entire selected dataset in order to obtain a database with corresponding curve descriptors. Also, at the a second database2 was created as a copy of the original database. Thus, the database2 has 30% of its descriptors randomly removed.

A neural regression network was trained using the database (original) as an output and the database2 (reduced) as an input, making the network to learn as reconstructing the calvaria region according to fig. 4. Fig. 4.a is the image with 30% of descriptors removed. Fig. 4.b is the original slice descriptors.



(a) (b)

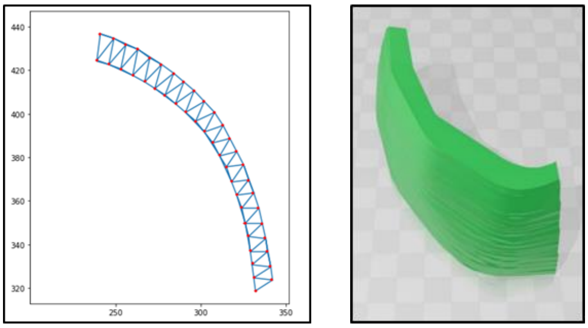
Figure 4. (a)Input descriptors. (b) Output descriptors.

Finally, to recover the lost part, it will be necessary to create the third database (database3), now only with the skull that you want to reconstruct. Some extra information will be needed such as Slice Location (0020, 1041) and Pixel Spacing (0028, 0030) obtained from the DICOM file, this information will serve for the correct geometric reconstruction.

Using the neural network that was previously trained, when predicting the lost descriptors from the third database, we have a set of new descriptors.

The descriptors of each layer of database3 were used to create the internal and external curves using the Cubic Splines method. From [11], each layer was connected to each other using triangles, as in fig.5(a) representing the connection of the points in a layer. Triangles allow us to create the 3D model that will be saved as an STL file.

With the 3D model ready and saved in STL it will be necessary to use the 3D builder software to prepare the file for printing. Fig.5(b) represents the model in the same proportions of the original.



(a) (b)

Figure 5. (a) Found curvature triangulation. (b) 3D superimposed curvature from reconstructed slices.

V. CASE STUDY

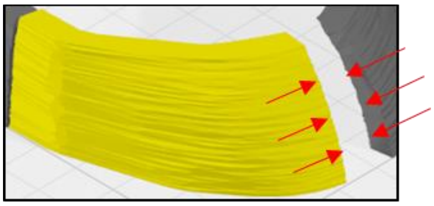
A study case was prepared in order to validate the performance of the method from an unknown image. The CT104 skull left out of the creation of the database was applied to all steps of the proposed methodology, i.e., the 60 descriptors per layer were obtained from the skull, 60 layers were used to create the model, where 30% of the descriptors were removed to perform the repair test. It was decided to remove the upper right region for comparison with other methods.

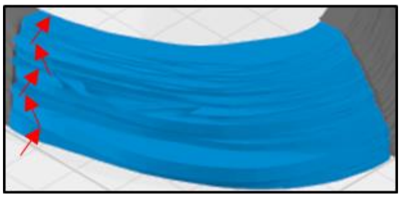
To compare the method using regressor networks (RN), the mirror method and the search method were also tested, the three methods were evaluated in terms of relative volume error. Table 1 shows the comparison, considering that the neural network was trained with 30 neurons and with fixed removal of 30%.

TABLE 1. COMPARISON OF METHODS

Method Type	**Error (%)**
Mirroring [3]	13.113
Searching [4]	1.609
RN (Modified GAN)	2.184

According to the mean error presented in table 1, the searching method had the best numerical result, and the mirroring method the worst, it is worth mentioning that the symmetry failed to reconstruct part of the frontal region. The model generated by each method was created in order to analyze the visual aspect and possible printing errors and can be seen in fig.6(a) mirroring model. Fig.6(b) searching model and fig.6(c) the modified GAN model called RN. All models were reconstructed by 3D Builder software in order to see the matching error in joining with the original bone.


(a)


(b)

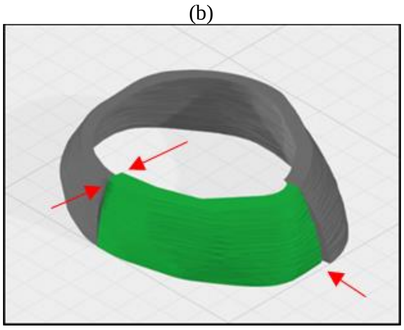

(c)

Figure 6. (a)Mirroring model. (b) Searching model. (c) Proposed Model

It is possible to notice the missing region in the model by mirroring method and the irregularity of the surface in the model by the searching method, which despite having the best numerical result ended up having a weak visual result. The proposed model shows a soft and regular surface, but it does not fit correctly on the original bone.

A second test performed was to calculate the error for each 10% of the fracture extension. According to table 2, the first training used 30 neurons and 30% removal of the descriptors, while the second training used 30 neurons and removal varying randomly between 10% and 40%.

TABLE 2. TRAINING MODE COMPARING

Removed (%)	**Train1 Error (%)**	**Train2 Error (%)**
10	26.313	5.951
20	13.439	3.243
30	2.184	**0.601**
40	8.952	2.415
50	25.913	5.175

Finally, the relative volume error was tested by varying the number of neurons, both networks were trained with fixed removal of 30% and the number of neurons according to table 3.

TABLE 3. THE AMOUNT OF NEURONS COMPARING

Removed (%)	**Neurons**	**Error (%)**
30	30	2.184
30	15	**1.231**

Fig.7 represents the 3D model obtained by RN network where 30% of the descriptors were removed.

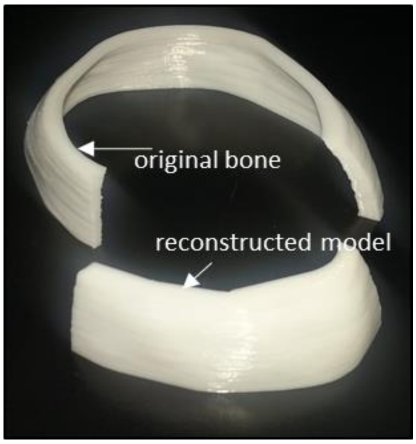


Figure 7. 3D models to printing.

VI. CONCLUSION

The use of neural networks has shown promise in solving the problem of modeling anatomical prostheses, with an error of 2.184% in the total volume, and it is important to note that the proposed technique presents visible errors in the interface region between the parts. With the comparison of the models it was possible to observe the difference between a more aesthetic solution and one purely based on percentage error.

The image processing techniques contributed to the reduction of the dimensionality of the images, which allowed the use of a simpler neural network. The relationship between percentage removed and number of neurons shows us that these parameters directly influence the quality of the finished model. Based on the knowledge acquired during the research it was possible to observe the need to repair the entire skull and even other bones, with the proposed method only elliptical or semi-elliptical regions can be recovered. For future investigations, the use of convolutional neural networks will be evaluated to reduce the dimensionality of the image, which replaces the curve descriptors, thus being an attempt at complete reconstruction and no longer slice by slice.

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