ANATOMICAL STRUCTURE SEGMENTATION IN CT AND MRI IMAGES FOR 3D MODEL GENERATION APPLIED TO ADDITIVE MANUFACTURING

ALEXANDRE SILVA LUCENA[1]; M.Sc. CLEITON DA GAMA GARCIA[2]; B.Sc. WILLIAM MELLO BORGONHI[3]; Prof. Dr. ELMER ALEXIS GAMBOA PEÑALOZA[4]; Prof. Dr. SIGMAR DE LIMA[5]

[1]Universidade Federal de Pelotas (UFPel) – alexandre.lucena@ufpel.edu.br
[2]Empresa Brasileira de Serviços Hospitalares (EBSERH) – cleiton.garcia@ebserh.gov.br
[3] Empresa Brasileira de Serviços Hospitalares (EBSERH) – william.borgonhi@ebserh.gov.br
[4]Universidade Federal de Pelotas (UFPel) – eagpenaloza@ufpel.edu.br
[5]Universidade Federal de Pelotas (UFPel) – sigmar.lima@ufpel.edu.br

1. INTRODUCTION

The segmentation of anatomical structures from medical imaging, such as Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) scans might play a crucial role in healthcare. The process permits 3D models originated from different sorts of biological tissue to be reconstructed, which can be used for various applications, such as personalized prosthetics (LEITE et al., 2019), educational purposes (BUFFINGTON; BAISH; EBENSTEIN, 2022) and even surgical (KONUTHULA et al., 2021) or radiotherapy planning (HARIRPOUSCH et al., 2024; CHEN et al., 2021).

Despite the wide range of segmentation techniques and its last advances, the best methods tend to perform very well on one type of medical image and underperform on others (ALZAHRANI; BOUFAMA, 2021). The human anatomy is very complex and subject to considerable variation. These factors, combined with the need for high precision, require sophisticated algorithms and techniques. In this context, recent advances in this area are based on deep learning techniques (HARIRPOUSCH et al., 2024; CHEN et al., 2021; TANG et al., 2019).

The most usual application for the anatomical segmentation is in distinguishing between healthy and diseased tissues, such as tumors (LIU et al., 2024). The accuracy of the process is essential for defining the precise boundaries of the tumor. In radiotherapy, for example, a good definition of the margins is crucial for healthy tissue preservation. Similarly, in surgical planning, a good delineation of cancerous tissues helps surgeons in preserving as much healthy tissue as possible, as demonstrated by OLSON, LY and MOHS (2018).

This paper aims to present the results of printed structures, originally in the form of CT and MRI scans. These structures were printed in Acrylonitrile Butadiene Styrene (ABS), an usual polymer for 3D printing. Furthermore, there is a wish to highlight the potential benefits of this process.

2. METHODOLOGY

The first step in the project involved collecting Digital Imaging and Communications in Medicine (DICOM) data. DICOM is a standard for storing and transmitting medical images and related information, ensuring interoperability between different systems and devices (NEMA, 2024). The data were obtained from public databases, such as InVesalius repository (INVESALIUS, 2024).

Segmentation process was performed using the open source software InVesalius, developed by the *Centro de Tecnologia da Informação Renato Archer*

(CTI), a Brazilian government agency. This software allows precise segmentation of different biological tissues from CT and MRI images. The approach to segmentation made use of conventional techniques such as edge-based, thresholding, and watershed methods, as highlighted in the review by ALZAHRANI and BOUFAMA (2021). After the segmentation, the surfaces were refined using Shapr3D, a 3D modeling software, to correct imperfections and make necessary adjustments. The model was then sliced for 3D printing in ABS using the Repetier software. Figure 1 illustrates the workflow from segmentation to 3D printing.

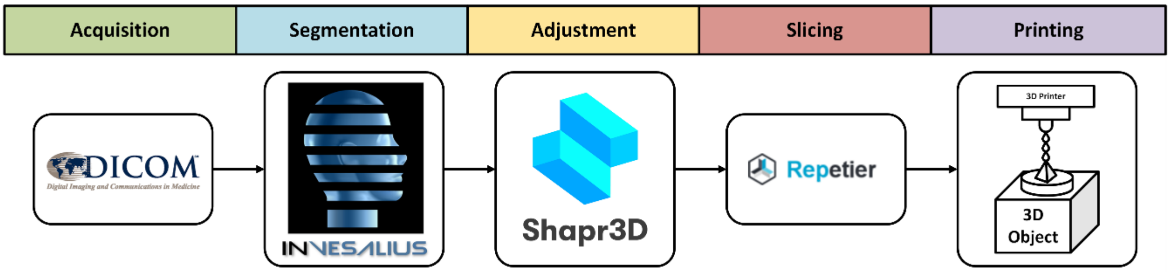

Figure 1: Segmentation and printing process

3. CT AND MRI PRINCIPLES

CT and MRI are widely used medical imaging techniques, each with distinct operating principles. According to BUSHBERG et al. (2011), CT uses X-rays to obtain cross-sectional images of the body, making it particularly effective at visualizing bones and dense tissues. In contrast, MRI employs magnetic fields and radiofrequency waves to produce detailed images of soft tissues, such as the brain, muscles, and internal organs. While CT involves exposure to ionizing radiation, MRI does not use radiation, making it a safer option. Figure 2 illustrates the difference between a head imaged by CT and a head imaged by MRI in the sagittal plane.

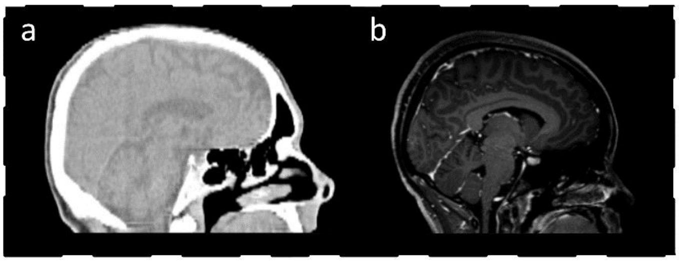

Figure 2: Sagittal plane images of a head: (a) CT scan (INVESALIUS, 2024) and (b) MRI scan (USP, 2024).

4. RESULTS

The printed models include a real sized cranium derived from a patient's CT scan, which shows a lesion. This demonstrates the accuracy of the segmentation and printing process in reproducing pathological features. Figure 3 and figure 4 illustrates the printed structures and the segmented view, respectively.

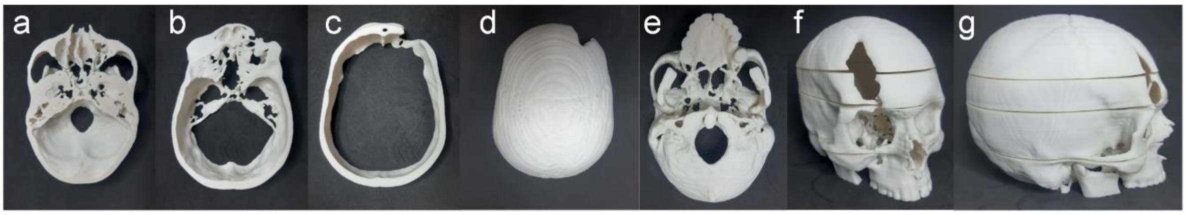

Figure 3:Different views and slices of the segmented and 3D-printed human skull. (a), (b), (c), and (d) are, from bottom to top, the layers of the skull printed separately. (e) is the bottom view of the lower layer, (f) is the angular view of the assembled skull

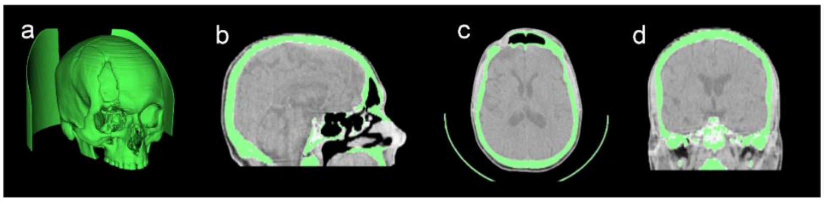

Figure 4: (a) 3D surface from segmentation (b) sagittal view mask (c) axial view mask (d) coronal view mask

To further demonstrate the segmentation and printing of soft tissues, a brain and a trachea were also printed. The brain was derived from the same CT scan as the cranium, while the trachea was derived from a CT scan of a chest. These are presented in Figure 5.

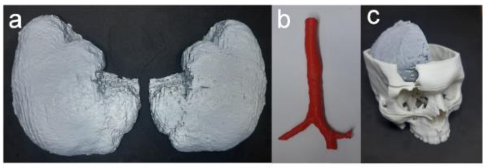

Figure 5: (a) Brain (b) trachea (c) cranium with one hemisphere of the brain fitted inside.

5. CONSIDERATIONS

The preliminary results are encouraging and demonstrate the potential of these techniques to enhance research or education. However, it is important to note that this project is in its early stages. Previous attempts by the team have been unsuccessful, highlighting the challenges associated to the process.

Future steps will focus on refining these methods and exploring the integration of advanced segmentation algorithms and tools to improve accuracy and efficiency. Potential applications include the production of models for medical analysis, educational purposes such as teaching anatomy, and simulation systems. These advances will be essential for achieving greater fidelity in 3D printed models and expanding their practical applications.

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