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AI-Driven Precision: Transforming Below-Knee Amputation Care in Modern Healthcare

Sarah Duraid AlQaissi[1], Ahmed A. AlDuroobi,[2]Abdulkader Ali. A. Kadaw[3]

Authors affiliations:
1) Department of Prosthetics and Orthotics, College of Engineering, Al-Nahrain University, Baghdad, Iraq.
st.sara.d.dawood.msc@ced.nahrainuniv.edu.iq

2) Department of Prosthetics and Orthotics, College of Engineering, Al-Nahrain University, Baghdad, Iraq.
ahmed.alduroobi@nahrainuniv.edu.iq

3) TU Bergakademie Freiberg, Institute for Machine Elements, Engineering Design and Manufacturing, 09599, Freiberg, Germany.
Abdulkader.Kadauw@imkffreiberg.de

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Abstract

Recently, three-dimensional models 3DM in the prosthetics field gained popularity, especially in the context of residual limb shape creation resulting from collecting medical images in Digital Imaging and Communications in Medicine DICOM format from a magnetic resonance imaging MRI after image processing accurately. In this study, a three-dimensional model of the residual limb for a patient with transtibial amputation was realized with the integration of artificial intelligence and a computer vision approach demonstrating the benefits of AI segmentation tools and artificial algorithms to generate higher accuracy three-dimensional model before prosthetic socket design or in case of comparison the 3D model generated from MRI with another 3D model generated from another technique, where a residual limb of a 23 years old male patient with amputation in the left leg wearing a prosthetic socket liner, and having 62 kg weight, 168 cm height, with high activity level. The patient was scanned using GE Medical Systems, 1,5 Tesla Signa Excite. MRI images in DICOM format were read to retrieve essential metadata such as pixel spacing and slice thickness. These images were processed to obtain a model that reflects the real shape of the residual limb using a specific algorithm, and the 3D model was extracted using AI segmentation tools. The obtained 3D model result with high resolution proves the potential of the artificial intelligence approach with deep learning to reconstruct 3D models concluding that AI has an instrumental role in medical image analysis, particularly in the areas of organ and tissue classification and segmentation., thus generating automatic and repetitive a 3D model.

Keywords: Artificial Intelligence, Deep Learning, Image Processing, Magnetic Resonance Imaging (MRI).

الدقة القائمة على الذكاء الاصطناعي: تحويل رعاية بتر تحت الركبة في الرعاية الصحية الحديثة

سارة دريد القيسي، أحمد عبد السميع الدروبي، عبد القادر علي عبد القادر قدو

الخلاصة:

في الآونة الأخيرة، اكتسبت النماذج ثلاثية الأبعاد 3DM في مجال الأطراف الصناعية شعبية خاصة في سياق إنشاء شكل الطرف المتبقي الناتج عن جمع الصور الطبية في التصوير الرقمي والاتصالات في الطب بتنسيق DICOM من التصوير بالرنين المغناطيسي MRI بعد معالجة الصورة بدقة. في هذه الدراسة، تم إنشاء نموذج ثلاثي الأبعاد للطرف المتبقي لمريض يعاني من بتر تحت الركبة من خلال دمج الذكاء الاصطناعي ونهج الرؤية الحاسوبية، مما يوضح فوائد أدوات التجزئة القائمة على الذكاء الاصطناعي والخوارزميات الاصطناعية لتوليد دقة أعلى ثلاثة -نموذج الأبعاد قبل تصميم السنخ الاصطناعي أو في حالة المقارنة، النموذج ثلاثي الأبعاد الناتج من التصوير بالرنين المغناطيسي مع نموذج ثلاثي الأبعاد آخر مولد من تقنية أخرى، حيث يتم وضع طرف متبقي لمريض يبلغ من العمر ٢٣ عامًا مصاب ببتر في الساق اليسرى ويرتدي بطانة سنخ صناعي، ويبلغ وزنها ٦٢ كجم، وطولها ١٦٨ سم، ومستوى نشاطها مرتفع. تم فحص المريض باستخدام GE Medical Systems، ١.٥ Tesla Signa Excite. تمت قراءة صور التصوير بالرنين

المغناطيسي بتنسيق DICOM لاسترداد البيانات التعريفية الأساسية مثل تباعد وحدات البكسل وسمك الشريحة. تمت معالجة هذه الصور للحصول على نموذج يعكس الشكل الحقيقي للطرف المتبقي باستخدام خوارزمية محددة، وتم استخراج النموذج ثلاثي الأبعاد باستخدام أدوات تجزئة الذكاء الاصطناعي. تثبت نتيجة النموذج ثلاثي الأبعاد التي تم الحصول عليها بدقة عالية إمكانية نهج الذكاء الاصطناعي مع التعلم العميق لإعادة بناء النماذج ثلاثية الأبعاد، وخلصت إلى أن الذكاء الاصطناعي له دور فعال في تحليل الصور الطبية، مع إمكانات هائلة في تصنيف الأعضاء/الأنسجة وتقسيمها، وبالتالي الحصول على DM٣ تلقائيًا وبشكل متكرر.

1. Introduction

In the prosthetic field, a discernible trend toward individualized patient care has emerged, notably in scenarios involving getting residual limb morphology. When addressing imaging modalities such as magnetic resonance imaging (MRI), and computer tomography (CT) scans, the delicate balance between ensuring patient safety and getting improved images to avoid re-scanning again stands as a pivotal consideration.

Prosthetics specialists benefit from the integration of image-guided interventions as they are crucial either in finite element analysis for determining loading conditions of segmented models derived from medical imaging [1], or in the study of the interference between the skin of the stump and the inner surface of the socket due to differences in geometric shapes, which is also known as overclosure [2]. Utilizing imaging modalities such as (CT) or (MRI) scans facilitates the acquisition of the internal and external surface and the bones of the residual limb [3], [4], [5] to reconstruct a three-dimensional (3D) model. Numerous methodologies are available for medical image segmentation, including traditional techniques based on regions and edges, as well as deep learning-driven approaches. Traditional methods face challenges stemming from non-uniform grayscale characteristics, unique individual differences, visual anomalies, and interference like image imperfections, and disturbances, furthermore, the time-consuming nature of 3D model creation, which demands the involvement of trained engineers, poses additional hurdles.

The cornerstone for crafting these 3D models hinges on image acquisition practices. Enhanced MRI scans have been recognized as the most dependable method for reconstructing the human body's muscles, tendons, and external morphology [6], [7]. Although in the past, the three-dimensional models were created automatically using specific radiological software, contemporary advancements have ushered in dedicated technologies enabling the development of highly precise and accurate 3D virtual reconstructions using artificial intelligence, utilizing professional software that can improve precision and ensure the integrity of the final model [8]. To overcome these challenges, the integration of artificial intelligence (AI) algorithms emerges as a pivotal solution, where AI, characterized by machines' ability to execute tasks and tackle issues without explicit programming, offers substantial promise in overcoming limitations associated with human factors [9]. Deep learning models have demonstrated remarkable efficacy in image segmentation, enhancing disease diagnosis precision and reducing extraneous computations. However, a recent systematic review and meta-analysis underscored that the specialty's comprehensive data accessibility through DICOM formats positions it uniquely for AI integration [10,11] to produce predictive models [12], potentially leading the way for AI advancements in other interventional fields such as diagnostic medical imaging [13,14] and analyzing patient data [15]. In medical technologies, Bitkina et al. identify the current state of artificial intelligence in medicine and prospects for future use [16]. In the prosthetics field, Deep Learning Models were used to Predict Prosthetic Ankle Torque [17], a machine-based model to detect the nominal alignment in transfemoral prosthetics [18], fuzzy logic-based modelling to forecast the impact of various surface reconstruction parameters on surface deviation response post transtibial prosthesis socket scanning [19]. In this study, a case was illustrated where artificial intelligence algorithms were employed to achieve a full reconstruction of the residual limb 3D model of a transtibial amputee, highlighting the accuracy and precision of the resulting 3D model, utilizing DICOM images from an MRI scan.

2. Materials and Methods

In this study, MRI images for a residual limb of a patient with transtibial amputation in the left leg (the age:23years, the weight: 62 kg, the height: 168 cm, sex: male with high activity level, amputated due to car accident, the level of the amputation is medium and wearing a prosthetic socket liner (ALPS Cushion Liner, HD Gel) with 6mm thickness (SPFR (HD)26-6), were utilized and taken by the GE Medical Systems, 1,5 Tesla Signa Excite, in Baghdad Scan Medical Center By Dr. A.G. Iraq. The test parameters values were set as follows: the series description T1 3D Axial, FOV of 23x23 cm, bitmap dimension 256x256 pixels obtained through repetition time (RT) = 5.052 (ms), echo time (ET)= 2.42 (ms) sequence, scan time 4 (min), slice thickness 3.0 (mm), distance between images 0.6 (mm). Images were acquired with a flexible phased-array surface coil wrapped around the limb. When a body segment is scanned, the MRI equipment captures images in the form of slices depending on the machine settings and the detail required. This single slice of information is filed in Digital Imaging and Communications in Medicine (DICOM) format. All DICOM data were exported to the application for processing and displaying medical images (RadiAnt DICOM Viewer 2023.1, Poznan, Poland). MRI slices were affected by noise due to the artifact caused by the little movement of the leg while taking the scan, causing a loss in detail quality, which requires preprocessing philtre to enhance clarity and definition. The 3D reconstruction was done followed by a volumetric reconstruction and a wrap, and then saved as stereolithography (STL) files (Fig. 1). It should also be noted that some problems occurred using the flexible coil device, whose integration with the MRI apparatus used for lower limb scanning was difficult; the magnetic core has a diameter of only Φ = 30 cm and requires horizontal leg positioning, while the system needs a little more volume to be fully performing to cover all the residual limb length.

3. Image Processing

After image acquisition, 244 images with 141 KB for each image were extracted, 14 were excluded due to the repetition and the included no feature, and 16 images were unable to be selected when imported into the 3D slicer 5.6.1 software (https://www. slicer.org/, accessed on 7 June 2023) Because of image noise and the difficulty of detecting the boundary of the end of the residual limb (Fig. 2). In the 3D slicer, the interested area of the images was enlarged using (Crop Volume for the region of interest ROI) (Fig. 3), the resulting images were saved in a DICOM format at 130 KB, and the noises of the images were reduced. The specific image processing to create a complete model for the residual limb is done by utilizing the pixel data information that is kept in the DICOM image header, which includes image resolution, slice instance number, slice thickness, etc. by new deep-learning methods for suppressing artifacts and improving overall quality. The data portion of the file contains pixel intensities arranged in rows, enabling accurate pixel placement after image processing with bitmap images matching the resolution and color details of the DICOM image. The rest of the image processing was completed using MATLAB algorithms and artificial intelligence (AI) tools. The overall fundamentals of digital image processing are shown in (Fig. 4) with 7 steps that are used for this study, including image reading, segmentation, processing, visualization, and mesh generation for further analysis or visualization. The process of image reading, and metadata extraction involves reading a DICOM image to retrieve essential metadata such as pixel spacing and slice thickness.

Subsequently, image segmentation techniques are employed, including (Otsu's thresholding) method. utilizing the (graythresh) function to create a binary image, followed by the conversion of the grayscale image to a binary format using the (imbinarize) function based on the determined threshold.

Further refinement is achieved through Canny edge detection applied to detect edges within binary images. The resultant processed images are stored in a 3D logical array, which is then converted to uint8 format for the purpose of saving the modified images. These modified images are then saved as DICOM files, ensuring that the updated metadata is included. For visualization purposes, the processed images are converted to single precision and visualized using the Volume Viewer tool. Additionally, surface mesh generation is conducted by creating an iso-surface from the processed images, adjusting vertex coordinates using metadata, and generating a triangulation object for the surface mesh. Following this, the surface mesh is plotted and displayed with specific visualization settings, and the faces and vertices of the mesh are saved as an STL file to facilitate their utilization in 3D modelling applications.

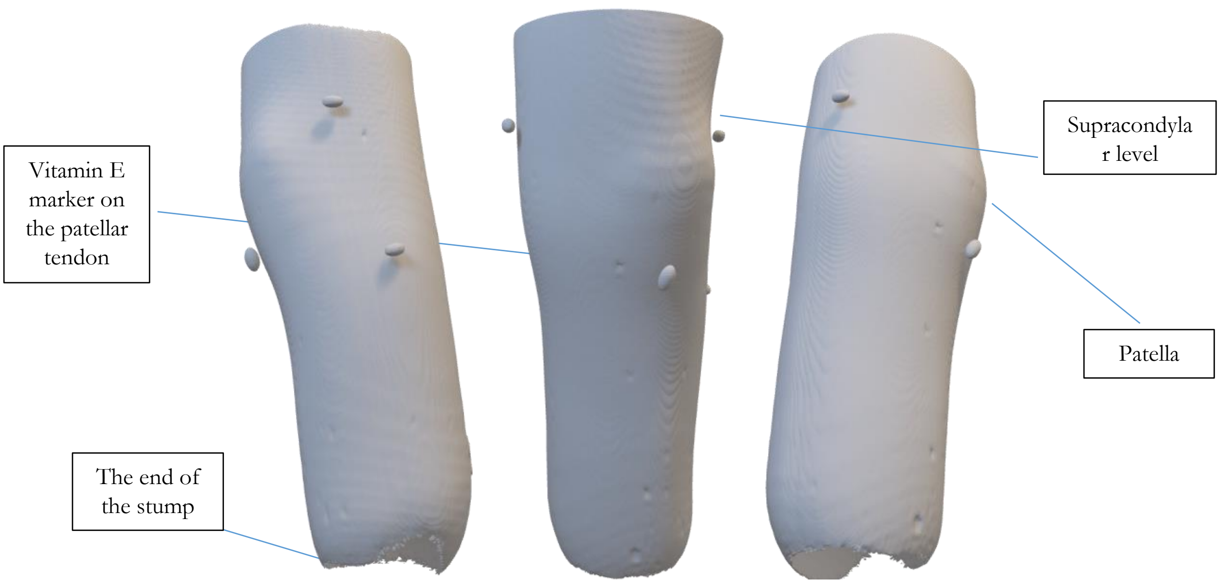

Figure (1): The 3D model has destruction from the end of the stump due to the coil size and the existence of the artifact.

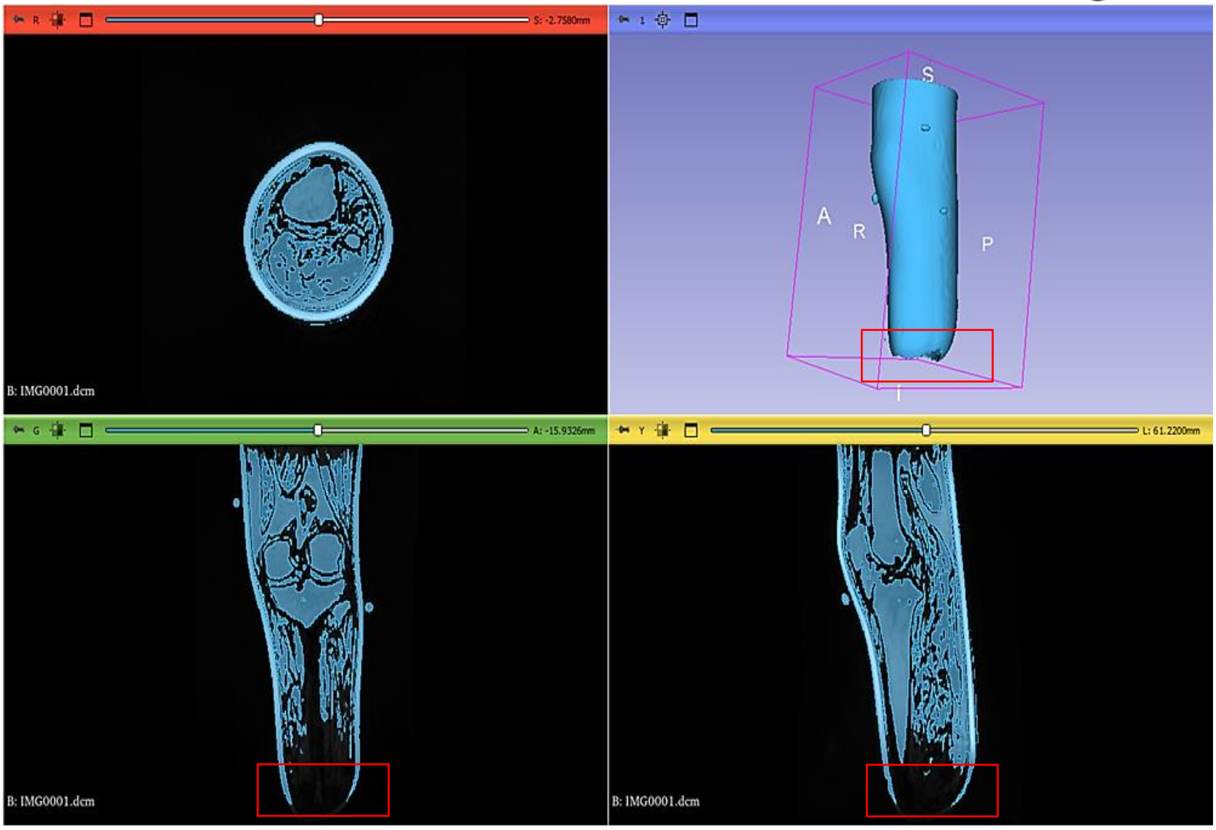

Figure (2): The noise of the images causes the difficulty of detecting the boundary of the end of the residual limb.

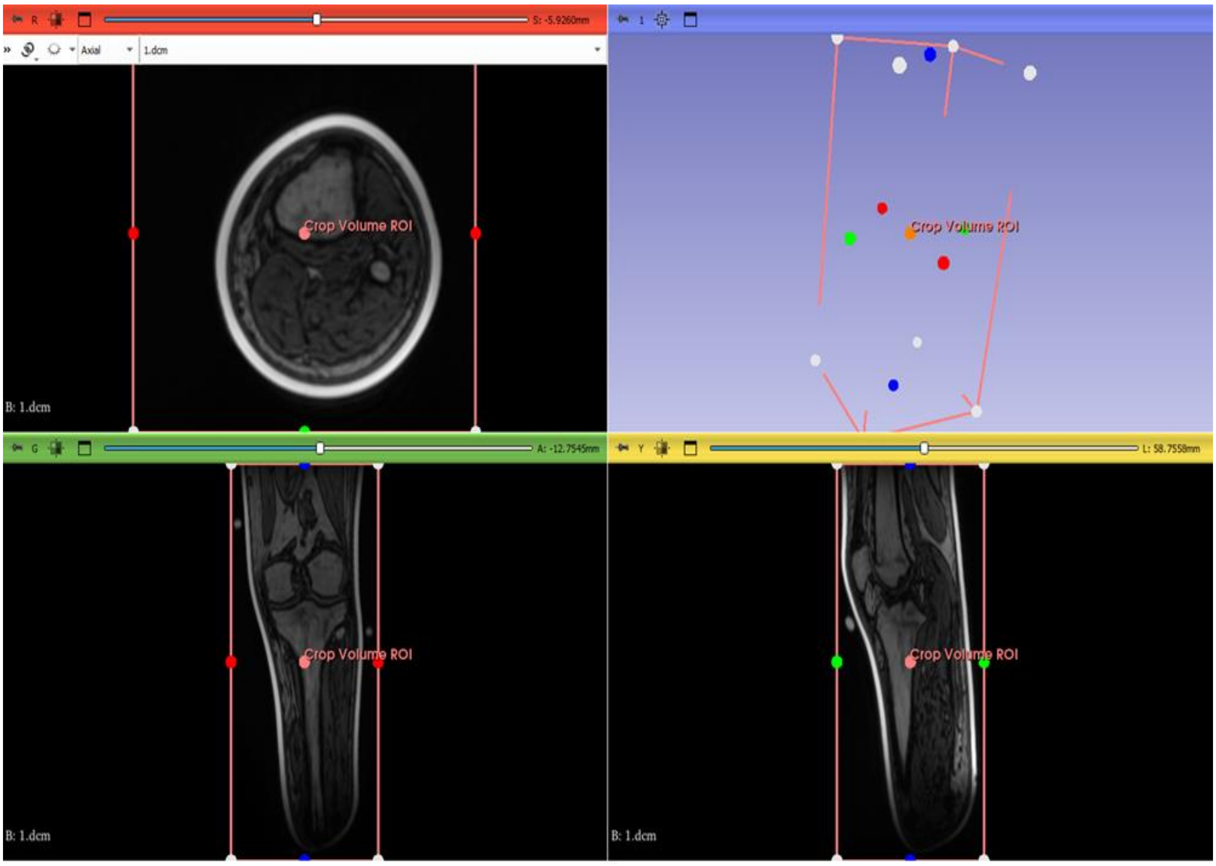

Figure (3): Using the Crop Volume function in 3D slicer to specify the interested area.

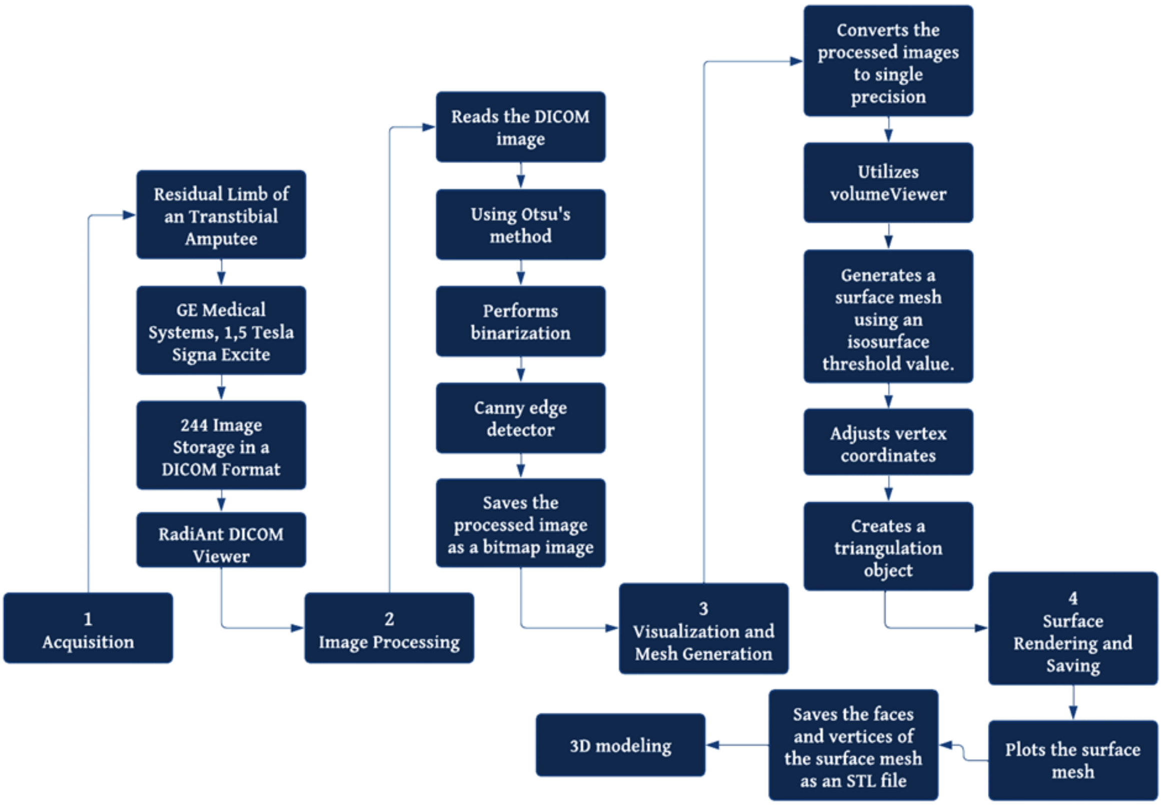

Figure (4): The fundamental steps of digital image processing.

4. 3D Reconstruction With AI

To achieve a three-dimensional model with increased precision, specifically tailored to the patient consisting of all residual limb structures including the end of the stump part, AI including deep learning was used based on the operative workflow demonstrated in (Fig. 5) that consists of five consecutive steps: Automated Metadata Extraction, Image Segmentation, Enhanced Image Processing, Intelligent Metadata Modification, Efficient Visualization and Mesh Generation.

By harnessing the capabilities of deep neural networks, the anatomical structures in medical images can be can now accurately classified and outlined, paving the way for automated 3D model reconstruction. This breakthrough has the potential to streamline processes in medical applications like diagnostic imaging and surgical planning. The role of artificial intelligence in this study is primarily focused on enhancing the efficiency and accuracy of medical image processing for DICOM images by automatically extracting and analysing metadata from DICOM files and enabling efficient data interpretation. AI algorithms aid in image segmentation by automatically identifying regions of interest, such as pixel spacing and slice thickness, crucial for medical image analysis. Using AI-powered techniques like thresholding and edge detection improves image processing accuracy and speed, contributing to more precise medical image analysis. AI facilitates the intelligent modification of metadata for new images, ensuring that essential information is correctly updated for further analysis and sharing.

Figure (5): The fundamental steps of digital image processing.

AI streamlines the visualization process and surface mesh generation by optimizing image data conversion and adjustment based on extracted metadata, enhancing the overall efficiency and accuracy of 3D model creation. The present case study seeks to explore the synergistic integration of cutting-edge computer vision techniques and state-of-the-art deep learning segmentation algorithms. As previously elucidated, the ambiguous slices encompassing the distal aspect of the residual limb were meticulously segmented through the employment of the 3D Slicer platform, leveraging a combination of automated and manual segmentation methodologies. These techniques harness the power of computer vision algorithms predicated on grayscale intensity values to delineate the anatomical structures of interest.

While the automated segmentation processes yield robust and consistent results, a degree of manual refinement is often necessary to further refine the contours of the anatomical structures to eliminate any erroneous "noise pixels" that may have been inadvertently included. By employing this approach, which capitalizes on the strengths of both automated and manual segmentation techniques, it was able to generate high-fidelity segmentation results.

5. Results

The Segmentation using 3D Slicer is an automatic tool based on AI. These cutting-edge algorithms are designed to accept any series of MRI scans as input and subsequently undertake the automated segmentation of a diverse array of anatomical structures of interest. The resulting 3D model after the segmentation of each one of the unclear slices in the end stump contains the end part of the residual limb but it is affected by noise due to the artifact caused by the little movement of the leg while taking the scan (the black circle) (Fig. 6). After 3D model construction, comprehensive images were re-processed using a proprietary algorithm. This algorithm meticulously re-processed each image, ensuring optimal quality and format compatibility. The processed images were then saved in the Bitmap (BMP) file format, a widely recognized standard for high-fidelity image representation. The new surface reconstruction that displays using code is more accurate and the details of the end of the stump can be observed (Fig. 7, a). The resulting model was saved in STL file format and loaded to software program Geomagic® Freeform® (333 Three D Systems, Circle Rock Hill, SC 29730, USA) to create a clay with no voids (Fig. 7, b), then the model loaded to Meshmixer (Autodesk, Inc., San Rafael, CA, USA) software for additional modifications including deleting non-interested areas, mesh, smoothing, and using the inspector tool to finish the modification process. (Fig. 7, c) demonstrated the final 3D model with a high accuracy and features that are needed to complete the shape of the residual limb.

6. Discussion

The creation of three-dimensional models with high accuracy is mainly in demand, especially with regard to the application of the medical field especially in prosthetics when dealing with patients with various amputations where the images of the residual limb have been obtained through medical imaging techniques such as magnetic resonance imaging MRI, Where authorized programs for medical application are used that are able to obtain hyper-accurate models.

However, this process is often burdened by numerous time-consuming and repetitive tasks, which can lead to diminished precision and a heightened risk of systemic errors. In this context, the advent of artificial intelligence (AI) plays a pivotal role, potentially offering engineers a transformative solution to these challenges.

The application of AI techniques alone has not allowed for generating 3D models suitable for prosthetic applications, particularly in achieving accurate residual limb shapes. This limitation necessitated the incorporation of additional algorithms, coupled with expertise in design software and meticulous adjustments, to meet minimal clinical requirements. The integration of AI with computer vision algorithms, however, shows great promise. It accelerates the modelling process and yields results comparable to the gold standard manual approaches while reducing dependence on operator intervention. In the future, further improvement of deep learning algorithms with multiple datasets training them to recognize more details will allow us to achieve optimal results, meeting clinical requirements and realizing detailed 3D reconstructions using artificial intelligence only.

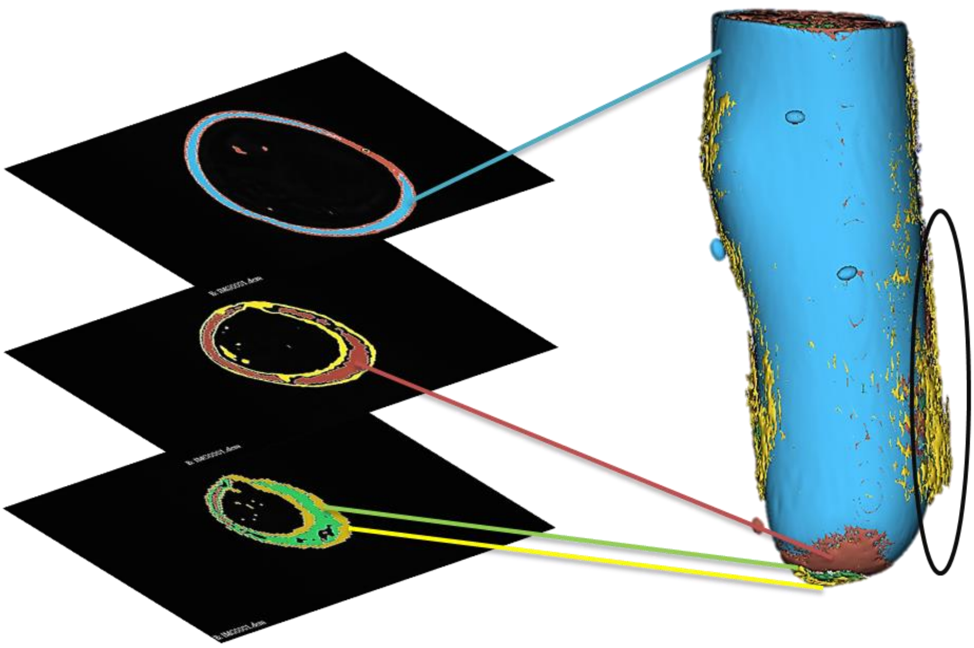

Figure (6): Artificial intelligence segmentation of the slices that include the end part of the residual limb was repeated to include all the missing parts in that area.

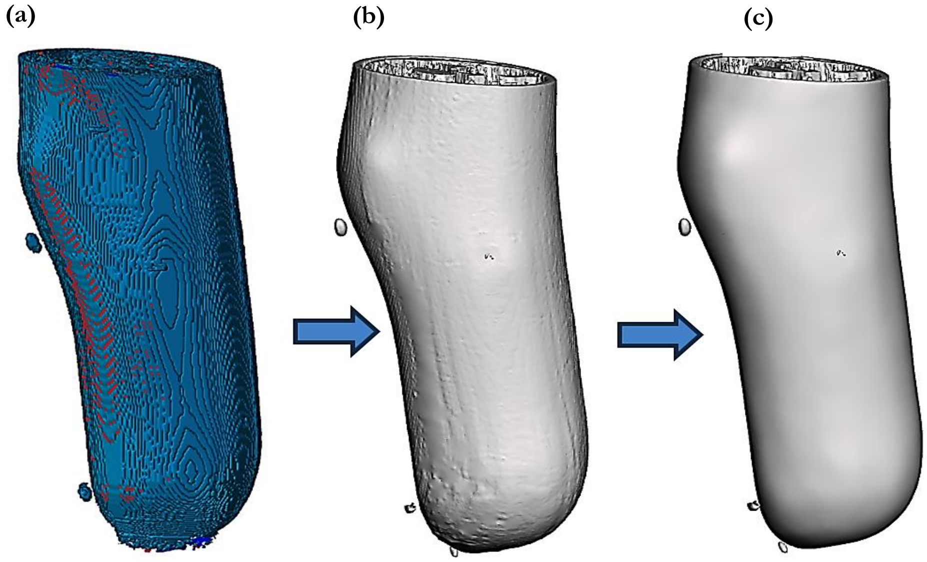

Figure (7): (a) The output model from the provided code that includes the pre-processing for all MRI slices saved in STL format. (b) The 3D model after being loaded into Freeform software. (c) the 3D model after additional modifications in Meshmixer.

Moreover, deep learning has the potential to be integrated into all stages of the modelling process, ensuring a consistent, repeatable quality standard that is independent of operator input. Nevertheless, it remains imperative that AI-generated results are verified by expert users to confirm their reliability and accuracy.

7. Conclusion

The integration of artificial intelligence (AI) with medical imaging has revolutionized the field of prosthetics, particularly in the creation of high-fidelity 3D models of residual limbs. The study presented herein demonstrates the potential of AI algorithms in enhancing the accuracy and efficiency of image segmentation and 3D reconstruction processes, as exemplified by the case of a transtibial amputee. The use of AI-driven tools, such as the Segmentation by 3D Slicer with an additional algorithm supported by AI, has shown promising results in automating the segmentation of MRI scans, thereby reducing the time-consuming manual tasks associated with traditional methods.

Looking ahead, the continuous refinement of deep learning algorithms and their integration with computer vision techniques hold the promise of fully automated, high-quality 3D model creation, which could significantly impact the field of prosthetics. This advancement could lead to better fitting prosthetic devices, improved patient outcomes, and a reduction in systemic errors associated with manual segmentation processes.

In conclusion, the synergy between AI and medical imaging represents a significant stride toward personalized patient care in prosthetics. As the technology matures, it is poised to become an indispensable tool in the hands of prosthetics specialists, enabling them to deliver more precise and efficient care to their patients. The future of AI in prosthetics is bright, and its full potential is yet to be realized.

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