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Study of 3D Reconstruction Techniques of Medical Scans in Healthcare

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ABSTRACT :

Through the use of 3D reconstruction techniques to medical images, the initiative aims to advance the field of medical imaging. This research attempts to create extremely detailed and dynamic three-dimensional representations from conventional two-dimensional medical images, such as computed tomography (CT) or magnetic resonance imaging (MRI) scans, by utilizing state-of-the-art technology. The suggested approach makes use of sophisticated computational models and algorithms to smoothly combine several cross-sectional scans, facilitating the production of an extensive and anatomically precise 3D reconstruction. This work is important because it can improve surgical planning, clinical diagnostics, and medical education by giving medical practitioners a more comprehensive and intuitive way to see complicated anatomical structures. This project aims to advance medical imaging through the integration of advanced image processing and computer graphics techniques, ultimately leading to better patient care and medical decision-making.

Keywords: Image Segmentation, Marching Cubes, 3D Reconstruction

Introduction :

The cutting-edge field of 3D reconstruction has become a potent tool in the field of medical imaging, converting two-dimensional images into complex three-dimensional representations. This innovative technology gives medical professionals a thorough grasp of anatomical structures in addition to improving diagnosis accuracy. By combining sophisticated imaging techniques with computer algorithms, 3D reconstruction creates a highly detailed reconstruction of medical scans, which enables a more in-depth examination of intricate structures including organs, bones, and tissues. This novel method helps with surgical planning, medical education, and correct diagnosis as well. Combining computing power with medical imaging raises the bar for healthcare quality and creates new opportunities for personalized medicine. This introduction explores how 3D reconstruction has a significant impact on medical scans and emphasizes how important it will be in determining the direction of therapeutic and diagnostic treatments in the future.

Literature Survey :

Paper [1] addresses the challenge of multi-organ segmentation in abdominal CT scans. While partially labeled datasets are easier to obtain, fully annotated data is necessary for traditional approaches, which might be challenging to obtain. A unique method using a conditional nnU-Net architecture is proposed in this research. The model's fundamental component is the nnU-Net. It presents a conditioning approach that adds another input layer to the decoder by feeding it auxiliary data. This conditioning improves the recovery of spatial information by enabling the model to include previous knowledge about organ classifications at the pixel level. The necessity for a more effective adaptive loss function is mentioned in the paper. The effectiveness and generalizability of the model can be impacted by the caliber and volume of accessible partially labeled data.

The [2] paper mentions the need to automate the segmentation of thoracic vertebrae from MRI scans to overcome the labor-intensive process of manual segmentation Ground-truth labels were generated for apical vertebrae in AIS patients and vertebra T9 in healthy participants Manual segmentation was carried out utilizing image analysis software. The automatic segmentation of vertebrae was achieved by the use of a deep learning network (UNet architecture). Using training data, data augmentation was used to depict visual alterations unique to various vertebral levels. Using the dice loss as the cost function and the Adam optimizer, the CNN was trained. The algorithm that was put into practice showed performance levels that were on par with those of human specialists. In particular, it obtained a mean Dice Score Coefficient (DSC) of 87%±4.3 for the vertebral levels T5–T12 of AIS patients. A higher DSC denotes more accuracy. DSC is a measure of the similarity between anticipated and ground-truth segmentations.

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Paper [3] indicates use of Edge computing and IOT to compute the medical scans of remote patient to segment and apply 3D Reconstruction for visualization of that part of body. The methods used in this study included gathering real-time data from Internet of Things devices as well as a variety of noisy CT scans. To get ready for the denoising procedure, these photos underwent preprocessing that included normalizing and the insertion of synthetic noise. In order to efficiently remove speckle noise while maintaining important image characteristics, we created a Multi-Stage Feature Extraction Generative Adversarial Network (MF-GAN). The Marching Cube technique, which is based on regional growth and trilinear interpolation, was then used to the denoised pictures to build a 3D reconstruction (RGT-MC). A primary limitation was the scarcity of a small dataset with a variety of high-quality noisy CT images, which may have affected how broadly applicable our results may be. Furthermore, training complex deep learning models such as MF-GAN was computationally demanding, which presented difficulties, especially for researchers with restricted access to high-performance computing resources.

The paper [4] mentions project “Med-3D,” is focused on applying the Structure-from-Motion technique, with the aid of transfer learning, to reconstruct 3D representations from medical images. The most likely goal of this study or research is to increase the precision and effectiveness of 3D reconstruction for use in medical applications. This study presents an approach that addresses the issues of limited data and supervision in 3D medical image reconstruction from 2D slices by combining transfer learning, SFM, view synthesis, and GAN-based optimization. The technique improves medical image analysis by utilizing information from natural images. Transfer Learning from Natural Images is one of the limitations. The domain gap between natural and medical images may not be completely addressed by transfer learning from natural images, despite its usefulness. To effectively bridge this gap, modern technologies frequently use domain-specific structures and domain adaption techniques. 1. Limitations Driven by Data: The approach is highly dependent on the availability of reliable and consistent 2D medical slices, which may not always be the case in practical situations. 2. Handling Limited Data: The study talks about using natural picture knowledge to get over data constraints, but it doesn't go into detail on how well this strategy works to solve the problems caused by a lack of medical image data.

Paper [5] aims to simplify the training process and leverage input data to supervise network predictions effectively. The goal of the research is to increase the accuracy and speed of 3D geometry reconstruction, especially in situations where there are intricate input representations. It is a potential method for 3D reconstruction problems since the neural networks in NDC and UNDC help forecast 3D mesh models from these inputs without requiring explicit gradient-based optimization. Restrictions: 1. Limited Input Types: Point clouds, signed or unsigned distance functions, and voxelized grids are among the common input forms that NDC is mainly intended to handle. Its applicability in situations where diverse input types are common may be limited by its potential unsuitability for other forms of 3D data formats2. Limited to 3D Data: NDC may not be immediately applicable to other sorts of data, such as 2D photos or non-geometric data, as it is intended for 3D geometry reconstruction.

Paper [6] deals with Converting 2D-Medical Image Files “DICOM” into 3D- Models, based on Image Processing, and Analysing their Results with Python Programming. The first pre- and during-process phase begins with file conversion, which goes through a number of internal stages. Next, import DICOM files and perform preprocessing to eliminate noise. Next, define the area to be modified by drawing a set of points and lines and carrying out adjustments to ascertain the internal points needed to show and address them. trimming, smoothing, and sculpting are the first steps before counting the number of polygons and figuring out how to display them properly and fluidly to display every detail. Verify the completed form in the second post-process phase before exporting it. If it matches exactly, there are two ways to export it as an OBJ file: first, follow the instructions in Table 2, Before and After Edit Segments, Resculpting & Trimming, above. A 3D simulation engine can use the generated 3D model. Return to the staged intended area and restore the same prior phase if there is nonconformity. Limitations: - This method is only applicable to MRI DICOM images; it is not suitable for CT scans or X-rays. - Not offering the patient a clear and simple method of receiving the 3D model

Paper [7] approach involves two neural networks for reconstruction work. Utilizing the structural properties of voxel matrices from MRIs, the first reconstruction chooses half as many slices for MRI rebuilding and super-resolution reconstruction. The rebuilding process is finished with a second reconstruction that fixes missing values in the rebuilt MRI using super-resolution technology. Among the restrictions are Scale Factor Challenge: The method is not flexible enough to accommodate arbitrary scaling factors, which suggests that it may not be able to handle a wide range of image sizes. Restricted to 2D Field: Although the approach reconstructs in 3D, it functions only in a 2D field, which may result in the loss of volumetric and depth features that are essential for some applications. Dependency on Supervised Learning: The study raises concerns about possible drawbacks to the present reliance on supervised learning techniques for MRI reconstruction, hinting to a move towards unsupervised learning in the future. Absence of Validation: There is no explicit validation of the article against clinical standards, which raises concerns regarding the validity and usefulness of the recreated images for medical diagnosis. Computational Complexity: There are questions over the method's efficiency, especially in a therapeutic situation, because its computational complexity is not addressed.

Paper [8] presents the U-Net architecture designed for biomedical image segmentation. The approach mainly uses data augmentation techniques to make effective use of a small number of annotated samples. The U-Net architecture consists of a symmetric expanding path for accurate localization and a contracting path to capture context. The segmentation of neural structures in electron microscopic stacks and cell tracking tasks utilizing phase contrast and DIC microscopy pictures were two of the difficulties the authors addressed this network to. They showed the network's greater performance over earlier techniques by training it end-to-end from a small number of photos. Among the restrictions are Restricted Noted Samples: The network's performance may be constrained by reliance on a narrow pool of annotated data because of the lack of dataset diversity. Task-Specific Performance: The efficacy of U-Net in a variety of biomedical segmentation problems is not assured by its performance in a given task. Absence of Supplementation Information Details: Performance on various datasets may be impacted by the lack of particular data augmentation techniques, which also hinders reproducibility. Absence of Error Analysis: The study does not include a thorough examination of U-Net's errors, which leaves out important information needed to enhance and modify the model.

Paper [9] deals with Deep recurrent adversarial network for automated pancreas segmentation. Two types of labels are used in this updated annotation method for pancreatic segmentation using Region Proposal Networks (RPNs): a modified red label to address class distribution imbalance and a green label for object-level annotation. For better segmentation accuracy, the red label seeks to balance the positive-to-negative sample ratio (about 1:3). Three steps are involved in the generation of the candidate region: first, the original label is modified to create the red label; second, pancreas CT scans and labels are fed into the RPN network to generate a region with high confidence; and third, the generated area and label are resized using nearest interpolation (e.g., 224x160). The performance of segmentation is improved by the introduction of area-sensitive candidate regions and red labels. Size calculations and recall are important criteria to consider when assessing this approach's efficacy. The work is limited because, while enough annotated training data can enable this task to achieve a competitive performance, large CT scan sizes (such as whole-tissue CT scans with nearly hundreds of millions of pixels) and the high costs associated with pixel-wise annotation typically result in the annotation of only a small subset of all CT datasets being available. Thus, in order to further enhance the functionality of our system, we will be using the unannotated pancreas CT scans in our future work.

Table 1 - Summary of Literature Survey for Image segmentation

References	Algorithm Used	Accuracy
[1]	nnU-Net	For Pancreas: 0.7918 For liver:0.9610 For Spleen:0.9648
[2]	U-Net	mean Dice Score Coefficient (DSC) of 87%±4.3 for the AIS patient vertebral levels T5-T12
[8]	U-Net	Intersection over Union (IOU) of 92% for 1 algorithm,second algorithm that attains 83%(IOU)
[9]	RPN	The method is successful in generating a single bounding box that surrounds the pancreas structure with almost 100% recall

Table 2 - Summary of Literature Survey for 3D Reconstruction

References	Algorithm Used	Accuracy
[3]	RGT-MC	90.7%
[4]	sfMLearner sfMLearner +CP Med-3D Med-3D +CP	97% 99% 85% 99%
[5]	NMC NDC UNDC	92.7% Parameter used Normalised 93.7% Cut (NC) 93.1%

Conclusion :

This study uses deep learning techniques in the field of development to increase 3D reconstruction of Medical scan in health care. From the study conducted we have concluded there is more scope in increasing the accuracy. The most common idea in the above paper is that the above researchers have used only a particular form of Scans. The future work may include focusing on developing more efficient algorithms or strategies to address computational complexity, making the technology accessible to a broader range of researchers. Future research may involve developing models that are versatile and effective across diverse biomedical segmentation challenges. Future work may include a software that can include all the medical scans for 3D Medical Reconstruction.

References :

[1]Guobin Zhang, Zhiyong Yang, Bin Huo, Shude Chai, Shan Jiang, Multiorgan segmentation from partially labeled datasets with conditional nnU-Net, Computers in Biology and Medicine, Volume 136, 2021, 104658, ISSN 0010-4825, https://doi.org/10.1016/j.compbiomed.2021.104658.

[2]M. Antico et al., “Deep Learning-Based Automatic Segmentation for Reconstructing Vertebral Anatomy of Healthy Adolescents and Patients With Adolescent Idiopathic Scoliosis (AIS) Using MRI Data,” in IEEE Access, vol. 9, pp. 86811-86823, 2021, doi: 10.1109/ACCESS.2021.3084949.

[3]J. Zhang, D. Li, Q. Hua, X. Qi, Z. Wen and S. H. Myint, “3D Remote Healthcare for Noisy CT Images in the Internet of Things Using Edge Computing,” in IEEE Access, vol. 9, pp. 15170-15180, 2021, doi: 10.1109/ACCESS.2021.3052469.

[4]H. Quan, J. Dong and X. Qian, “Med-3D: 3D Reconstruction of Medical Images based on Structure-from-Motion via Transfer Learning,” 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Houston, TX, USA, 2021, pp. 1051-1056, doi: 10.1109/BIBM52615.2021.9669599.

[5]Neural Dual Contouring “Neural Dual Contouring” refers to a technique or approach that likely combines neural networks with the dual contouring algorithm to address problems related to 3D geometry reconstruction or modelling, doi: 10.1145/3528223.3530108

[6]Converting 2D-Medical Image Files “DICOM” into 3D- Models, based on Image Processing, and Analysing Their Results with Python Programming, doi: 10.37394/23205.2020.19.2

[7]Z. Hongtao, Y. Shinomiya and S. Yoshida, “3D Brain MRI Reconstruction based on 2D Super-Resolution Technology,” 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Toronto, ON, Canada, 2020, pp. 18-23, doi: 10.1109/SMC42975.2020.9283444.

[8]U-Net: Convolutional Networks for Biomedical Image Segmentation, doi: 10.48550/arXiv.1505.04597.

[9]Ning, Yang; Han, Zhongyi; Zhong, Li; Zhang, Caiming: ‘DRAN: Deep recurrent adversarial network for automated pancreas segmentation’, IET Image Processing, 2020, 14, (6), p. 10911100, doi: 10.1049/iet-ipr.2019.0399 IET Digital Library.