A Review Paper on Automation of Dicom Image Segmentation

Sanchez Innocencia Dass*, M. Marimuthu

Department of Computing, Coimbatore Institute of Technology, Coimbatore, India

Review Article

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***For Correspondence :** Sanchez Innocencia Dass, Department of Computing, Coimbatore Institute of Technology, Coimbatore, India, Tel: 7871163390;

Email: sanchezinno1@gmail.com

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ABSTRACT

DICOM is been used worldwide to exchange, store and transmit medical images. DICOM image segmentations are organized as a list of segments, in which each segment corresponds to a separate object that has been segmented. This paper deals with a comprehensive

e study on the automatic segmentation process of the DICOM Images using image processing techniques. The DICOM Segmentation can be done using some medical software which has been mainly designed for the Segmentation of the DICOM Images by either using programming languages or manually using the software itself. The methods of machine learning and deep learning plays a vital role in the process of segmentation as this process is one of the Learning techniques which is being used widely spoken phrase in this era. One of the Deep Learning Algorithms called the Convolutional Neural Network (ConvNet/CNN) takes up the input image and assign importance to various aspects in the image which can be differentiated from one another. The reviews were taken from the journal articles consisting of the process of Segmentation of the DICOM Images of Brain and Skull from the imaging modalities like radiography, ultrasonography, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Angiography. The Analysis of the process of segmentation using programming languages like Python, C++ and MATLAB was done based on the review articles. Finally, discussed on the machine learning techniques which would be suitable for the implementation process and also discussed on the programming languages that can be used for the process of segmentation and also the medical segmentation software that has been taken into consideration.

INTRODUCTION

Digital Imaging and Communications in Medicine (DICOM) is the standard for management and communication of medical imaging information and related data [1]. A DICOM image incorporates standards for some imaging modalities like radiography, ultrasonography, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Angiography. DICOM Segmentations are organized as a list of segments, where each segment corresponds to a separate object or label being segmented. Segments can overlap (i.e.) a single voxel of the source image can have multiple labels [2]. Each segment contains information on what it describes, and also what method was used to generate it. Segmentation of DICOM Images is of many types like the thresholding segmentation, edge-based segmentation, region-based segmentation, watershed segmentation, clustering-based segmentation algorithms, and neural networks for segmentation. From the above methods, thresholding segmentation is one of the easiest and user-friendly image segmentation methods [3].

LITERATURE REVIEW

Belma Dogdas, et.al in the paper segmentation of skull and scalp in 3-D human MRI using mathematical morphology have presented a new technique for segmentation of skull and scalp in T1-weighted Magnetic Resonance Images (MRIs) of the human head [4]. Their method uses mathematical morphological operations to generate realistic models of the skull, scalp, and brain that are suitable for Electro Encephalo Graphy (EEG) and Magneto Encephalo Graphy (MEG) source modeling. They have also used the scalp mask in the skull segmentation procedure, as it allows us to automatically exclude background voxels with intensities similar to those of the skull and then have found the inner and outer skull boundaries using thresholding and morphological operations. Dice Coefficient has been used to measure the MRI Skull Segmentation accuracy in a quantitative comparison [5].

Yuka Sen, et al. in the paper development of image segmentation methods for intracranial aneurysms provided vital means for the visualization, diagnosis, and quantification of decision-making processes for the treatment of vascular pathologies, vascular segmentation remains a process that continues to be marred by numerous challenges. In their study, they validate eight aneurysms *via* the use of two existing segmentation methods; the region growing threshold and chan-vese model. Based upon this validation study, they have proposed a new Threshold-Based Level Set (TLS) method in order to overcome the existing problems. With divergent methods of segmentation, they discovered that the volumes of the aneurysm models reached a maximum difference of 24% [6]. The proposed TLS method holds the potential for utilization in automatic aneurysm segmentation without the setting of a seed point or intensity threshold. This technique will further enable the segmentation of anatomically complex cerebrovascular shapes, thereby allowing for more accurate and efficient simulations of medical imagery.

Neeraj Sharma and Lalit M. Aggarwal in the paper automated medical image segmentation techniques has discussed on the accurate segmentation of medical images which is a key step in contouring during radiotherapy planning [7]. Computed Topography (CT) and Magnetic Resonance (MR) imaging are the most widely used radiographic techniques in diagnosis, clinical studies and treatment planning. This review provides details of automated segmentation methods, specifically discussed in the context of CT and MR images. They have also discussed on the problems encountered in segmentation of CT and MR images, and the relative merits and limitations of methods currently available for segmentation of medical images.

Shirly, S and Ramesh, K in the paper review on 2D and 3D MRI image segmentation techniques has discussed on the commonly used segmentation techniques are threshold-based image segmentation, clustering based image segmentation, edge-based image segmentation, region-based image segmentation, atlas-based image segmentation, and artificial neural network-based image segmentation [8]. Also exclaimed that Image segmentation is an image processing technique which is used for extracting image features, searching and mining the medical image records for better and accurate medical diagnostics. This comparative study summarizes the benefits and limitations of various segmentation techniques.

Aaron Fenster and Bernard Chiu in their paper of evaluation of segmentation algorithms for medical imaging has described an approach to be used for medical image segmentation evaluation. The process for segmenting organs and structures from medical images is gaining increased importance in the diagnosis of diseases and in guiding minimally invasive surgical and therapeutic procedures. Also, they have exclaimed that choosing an appropriate effectiveness measure of object segmentation is a difficult task and weighting the importance of different possible performance metrics requires matching the metrics to the segmentation objectives [9]. In this paper, we review those three types of metrics must be measured and reported: accuracy, precision and efficiency.

Dominik Müller and Frank Kramer in the paper MIScnn: a framework for medical image segmentation with convolutional neural networks and deep learning in their work have pushed towards constructing an intuitive and easy-to-use framework for fast setup of state-of-the-art convolutional neural network and deep learning models for medical image segmentation. The aim of the framework is Medical Image Segmentation with convolutional neural networks (MIScnn) to provide a complete pipeline for preprocessing, data augmentation, patch slicing and batch creation steps in order to start straightforward with training and predicting on diverse medical imaging data. Additionally, it facilitates a simple deployment and fast usage of new deep learning models for medical image segmentation [10]. Still, MIScnn is highly configurable to adjust hyper parameters, general training parameters, preprocessing procedures, as well as include or exclude data augmentations and evaluation techniques.

Jordi Minnema, et.al in the paper CT image segmentation of bone for medical additive manufacturing using a convolutional neural network presented a study to develop and train a Convolutional Neural Network (CNN) for bone segmentation in Computed Tomography (CT) scans, where the most tedious and time-consuming task in medical Additive Manufacturing (AM) is image segmentation. The method they have used is the CNN trained with CT scans acquired using six different scanners. The CNN segmented all patient CT scans using a leave- 2-out scheme. All segmented CT scans were converted into STL models and geometrically compared with the gold standard STL models [11]. The fully-automated CNN was used to accurately segment the skull. CNNs thus offer the opportunity of removing the current prohibitive barriers of time and effort during CT image segmentation, making patient-specific AM constructs more accessible.

Alireza Norouzia, et.al, in the paper medical image segmentation methods, algorithms, and applications has told that the importance of image processing is image segmentation. Many image segmentation methods for medical image analysis have been presented in this paper. In this paper, they have described the latest segmentation methods applied in medical image analysis [12]. The advantages and disadvantages of each method are described besides examination of each algorithm with its application in magnetic resonance imaging and computed tomography image analysis. Each algorithm is explained separately with its ability and features for the analysis of grey-level images. In order to evaluate the segmentation results, some popular benchmark measurements were presented.

Bingjiang Qiu, et.al, in their paper automatic segmentation of the mandible from computed tomography scans for 3D virtual surgical planning using the convolutional neural network has talked about segmentation of mandibular bone in CT scans which is a crucial for 3D virtual surgical planning of craniofacial tumor resection and free flap reconstruction of the resection defect, in order to obtain a detailed surface representation of the bones. Segmentation of mandibles in CT scans is influenced seriously by metal artifacts and large variations in their shape and size among individuals. The approach adopts the architecture of the U-Net and then combines the resulting 2D segmentations from three orthogonal planes into a 3D segmentation [13]. Experimental results show that their proposed approach for mandible segmentation in CT scans exhibits high accuracy.

Feng Jiang, et.al, in the paper medical image semantic segmentation based on deep learning has been extensively studied on the image sematic segmentation. The modern methods rely on the deep convolutional neural networks, which can be trained to address this problem. In this paper, we address medical image semantic segmentation problem by applying the modern CNN model [14]. Moreover, the recent achievements in deep learning allow processing the whole image per time by applying concepts of the fully convolutional neural network. Their qualitative and quantitate experiment results demonstrated that modern CNN can successfully tackle the medical image semantic segmentation problem.

Saleha Masood, et.al in the paper a survey on medical image segmentation explained medical image segmentation is a sub field of image segmentation in digital image processing that has many important applications in the prospect of medical image analysis and diagnostics. Here in this paper different approaches of medical image segmentation have been classified along with their sub fields and sub methods. Segmentation is a process in which an image is divided into several sub regions based on a specific feature in order to pick up a region of interest. Segmentation process has enormous applications in the medical field. In the field of research and development much work has been done to overcome the problems faced by the segmentation process and yet there is a need of more effective and efficient work.

Carlos E Cardenas, et.al in their paper of advances in auto-segmentation has described manual image segmentation is a time-consuming task routinely performed in radiotherapy to identify each patient's targets and anatomical structures. The efficacy and safety of the radiotherapy plan requires accurate segmentations as these regions of interest are generally used to optimize and assess the quality of the plan. Automatic segmentation (or auto-segmentation) of targets and normal tissues is, therefore, preferable as it would address these challenges. Previously, auto-segmentation techniques have been clustered into 3 generations of algorithms, with multitask based and hybrid techniques (third generation) being considered the state-of-the-art. In this paper, the authors review traditional (no deep learning) algorithms particularly relevant for applications in radiotherapy. Concepts from deep learning are introduced focusing on convolutional neural networks and fully-convolutional networks which are generally used for segmentation tasks [15]. Furthermore, the authors provide a summary of deep learning auto-segmentation radiotherapy applications reported in the literature. Lastly, considerations for clinical deployment (commissioning and QA) of auto-segmentation software are provided.

Qifei Dong, et.al in the paper dicom annotator: a configurable open-source software program for efficient DICOM image annotation has described that modern, supervised machine learning approaches to medical image classification, image segmentation, and object detection usually require many annotated images. Ideally, this program should be configurable for various annotation tasks, enable efficient placement of several types of annotations on an image or a region of an image, attribute annotations to individual annotators, and be able to display Digital Imaging and Communications in Medicine (DICOM)-formatted images [16]. In this paper, they present the design and implementation of dicomannotator. using spine image annotation as a test case, their evaluation showed that annotators with various backgrounds can use DicomAnnotator to annotate DICOM images efficiently.

DISCUSSION

Santiago González Izard, et.al in the paper Next med: Automatic imaging segmentation, 3D reconstruction, and 3D model visualization platform using augmented and virtual reality explained the visualization of medical images with advanced techniques, such as augmented reality and virtual reality; represent a breakthrough for medical professionals [17]. To visualize medical images in 3D, the anatomical areas of interest must be segmented. Currently, manual segmentation, which is the most commonly used technique, and semi-automatic approaches can be time consuming because a doctor is required, making segmentation for each individual case unfeasible. Using new technologies, such as computer vision and artificial intelligence for segmentation algorithms and augmented and virtual reality for visualization techniques implementation, they have designed a complete platform to solve this problem and allow medical professionals to work more frequently with anatomical 3D models obtained from medical imaging [18]. As a result, due to the different implemented software applications, permits the importation of digital imaging and communication on medicine (dicom) images on a secure cloud platform and the automatic segmentation of certain anatomical structures with new algorithms that improve upon the current research results.

Alain Jungo, et.al in the paper pymia: A Python package for data handling and evaluation in deep learning-based medical image analysis provides data handling and evaluation functionalities. The evaluation allows stand-alone result calculation and reporting, as well as performance monitoring during training using a vast number of domain-specific metrics for segmentation, reconstruction, and regression [19]. The pymia package is highly flexible, allows for fast prototyping, and reduces the burden of implementing data handling routines and evaluation methods. The developed package was successfully used in a variety of research projects for segmentation, reconstruction, and regression [20,21].

Mohammad Hesam Hesamian, Wenjing Jia, Xiangjian He and Paul Kennedy in the paper of deep learning techniques for medical image segmentation: achievements and challenges established as a robust tool in image segmentation by deep learning-based image segmentation [22,23]. In this article, they present a critical appraisal of popular methods that have employed deep-learning techniques for medical image segmentation. Medical image segmentation, identifying the pixels of organs or lesions from background medical images such as CT or MRI images, is one of the most challenging tasks in medical image analysis that is to deliver critical information about the shapes and volumes of these organs. Many researchers have proposed various automated segmentation systems by applying available technologies. The promising ability of deep learning approaches has put them as a primary option for image segmentation, and in particular for medical image segmentation [24].

Takashi Kamio, et.al in the paper DICOM segmentation and STL creation for 3D printing: a process and software package comparison for osseous anatomy they focus and report on the DICOM to STL segmentation performance for nine software packages. Extracting and three-Dimensional (3D) printing an organ in a region of interest in DICOM images typically calls for segmentation as a first step in support of 3D printing. The DICOM image file was then segmented and exported to an STL file using nine different commercial/open-source software packages. Once the STL models were created, the data (file) properties and the size and volume of each file were measured, and differences across the software packages were noted [25]. The data (file) size of the STL file and the numbers of triangles that constitute each STL model were different across all software packages.

CONCLUSION

From the reviews above, we find that image segmentation is one of the image processing techniques and that is being widely used in medical sectors for the segmentation of DICOM Images. Also, have resources have Python programming has been used to segment the DICOM Images. We have also got to know that there are many segmentation techniques and algorithms in image processing for image segmentation. And also, evaluation algorithms also play a vital role as to verify the segmentation of the DICOM images. The deep learning technique, Convolutional Neural Network (CNN) can tackle the medical image semantic segmentation problem successfully. The ability of deep learning approaches has put them as a primary option for image segmentation, and in particular for medical image segmentation. Thus, I conclude that deep learning techniques and segmentation algorithms play a vital role in the process of image segmentation. This can also be applied in software's like Python, MATLAB, C++ etc., and the process can be automated and easier for the medical scientists to have a clear view by making a comparison of the 3D model and the DICOM images.

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