Preoperative Image Segmentation For Organ Visualization Using Augmented Reality Technology During Open Liver Surgery

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***Abstract*— With the emergence of Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), three-dimensional images facilitate the generation of 3D models of a patient, providing a new practical and accurate assistance, particularly for surgical planning. These images can be manipulated to produce an accurate 3D representation of an organ. The reconstructed mesh can be used to generate and visualize a deformable model during surgical intervention using Augmented Reality (AR) technology. To obtain an efficient reconstruction, a segmentation of these medical images using deep learning architecture can be used to extract the target organ's properties. Many methods were proposed based on the captured pre-operative patient's CT scans. Generally, the segmentation process is done manually using image processing software. In this context several approaches were proposed, these methods are not efficient and need human interaction to select the segmentation area correctly. This work aims to develop a deep learning method using a Convolutional Neural Network (CNN) that captures the liver organ from a set of CT scans. Given preoperative patient-specific data (CT scans), the U-net architecture is implemented to detect the liver organ. As a result, the segmented 2D images are used to generate a 3D patient-specific liver model.**

Keywords*— Augmented Reality, 3D model reconstruction, Medical imaging, Open surgery, CT scans, Deep learning, Python.

I. Introduction

Liver is a vital organs in the human body, it maintains proper cyclic functioning of the body. The liver has a wide range of functions, including protein synthesis, numerous metabolites detoxification [1]. Due to its importance, the liver is exposed to various diseases, it is subject to many pathologies, including hepatitis B and C, that can escalate into fatal diseases, such as cancer or cirrhosis. According to [1], Liver cancer is the fifth most diagnosed cancer and the second most deadly cancer. For decades, liver open surgery remains the primary treatment for these kinds of diseases. In this type of surgery, CT scans are commonly used to extract anatomical and pathology-related information that can serve to properly diagnose the surgical site. Due to the complexity, blurred background, and shape of the internal human organs, manually processing and extracting the target organ from the medical images is a laborious and time-consuming process even for experts. Therefore, the study of automated liver segmentation is a key component of liver surgery and has significant practical relevance. Several researchers study the possibility to improve the effectiveness and efficiency of medical images segmentation. An automatic segmentation with high accuracy remains a challenging task, given the contrast difference between different tissue shapes within the image. In addition, the liver intensity is very similar in comparison with the neighboring organs such as the heart and the stomach. Moreover, liver pathologies such as Cirrhosis that often occur in the medical images vary in shape, texture, and intensity from patient to patient. These factors make it difficult to get an accurate segmentation of the liver from the existing approaches, as they can not be applied for clinical diagnosis during liver treatment.

Recently, Deep learning techniques became dominant in medical imaging approaches. Especially Convolutional neural networks that are used to automatically divide CT scans to localize a target region. This paper proposes an automatic segmentation approach based on Convolutional Neural Network to accurately segment the liver shape from patient-specific CT scans. Our method was tested with a set of CT scans acquired from the 3DIRCADb dataset [2]. The obtained results are validated by different quality measures. This paper is organized as follows: first, a literature review of different 2D segmentation techniques, is presented. Next, the proposed approach is described. Then, the obtained results are highlighted and discussed. Conclusion and perspective are presented at the end.

II. State of the Art

In order to obtain accurate segmented images, Image pre-processing is a required step in the medical images analysis approach that is used to improve the quality of the raw input image. It involves noise reduction, enhancement, normalization, and standardization procedures. Pre-processing is critical to the efficacy of subsequent processes, since defining blocks and feature extraction are all reliant on image quality. In order to provide an effective diagnosis of human diseases and abnormalities, many pretreatment methods rely on preoperative data from CT and MRI images are used. These preoperative scans are crucial for identifying the type of disease in order to plan surgery and radiotherapy. Several methods such as mean filtering, adaptive mean

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filtering, order-statistic filtering, adaptive weighted median filtering, maximum a posteriori filtering, nonlinear diffusion, and geometric filtering [3][4][5] are used to reduce the effects of noise caused by the CT scanners. Mean filtering replaces each pixel with the mean value of its neighbors. It produces the impression of picture smoothing and blurring [5]. To identify and retain edges and features, the adaptive mean filtering approach employs local picture statistics such as mean and variance [6]. Additionally, this method reduces the noise effect by substituting it with the local mean value. This filter adjusts the characteristics of the image locally and aids in the selective reduction of noise from different regions of the image [7]. Geometric Filtering minimizes noise while preserving key details. It employs a non-linear, iterative algorithm to modify the value of neighboring pixels based on their relative value [8]. Another approach involves the usage of neural networks to process the input images.

Several reconstruction methods are implemented to obtain an efficient 3D model from input CT scans [9]. In the literature, volumetric medical images such as CT scans and MRIs are well established for medical diagnosis of hepatic diseases. However, the amount of data generated by high-resolution CT scanners, as well as the time required to evaluate the resultant thousands of slices, has been increasing rapidly, making the analysis of radiologists and physicians more difficult and time-consuming.

Recent advances in CT technology and image segmentation methods led to the development of new solutions implementing machine learning and deep learning techniques that aim for accurate liver segmentation. Multiple studies were focused on implementing specific algorithms for upscaling to enhance the image features and noise filtering [10]. Lu et al. [11] provide a technique for locating the liver by removing slices that do not include liver tissue from the volume. However, the elimination of the slices is done manually, this technique is still limited. Deep learning has recently become one of the most popular approaches. CT scans were automatically divided using convolutional neural networks to segment regions around the liver area. Sugimori [12] conducted research employing deep learning to identify the brain in different slice locations with contrast-enhanced and plain imaging, CT images of the brain, neck, chest, abdomen, and pelvis were classified into ten classes. For image classification, the AlexNet and GoogLeNet architectures were trained and evaluated. These architectures were designed to classify natural images rather than medical ones. Clustering-based techniques are founded on the idea that in n-dimensional feature space, the distance and similarity between samples belonging to the same class are short and high, respectively. Clustering-based techniques are entirely automated and capable of doing multiple segmentation. Fuzzy c-means (FCM) and k-means clustering are commonly used in these approaches. FCM was used by Zhao et al. [13] to conduct initial segmentation, which was later smoothed by morphological processing methods. When compared to K-means, FCM is more effective at entirely segmenting the liver and can also be used to improve the rough segmentation. Using K-means, Foruzan et al. [14] calculated the starting border of the active contour. Other clustering approaches for MRI images include hierarchical clustering and self-organized maps [15].

Nasrullah et al. [16] presented a technique that uses a 2D convolutional neural network with a sliding window approach to locate lung nodules. After the lungs have been separated using a 64 by 64 pixel sliding window using a 24-pixel overlay. The 64 by 64 window is fed into the 2D convolutional neural network classifier, which conducts binary classification to determine whether the window is positive or negative. Christ et al. [17] reported an automated segmentation technique using cascaded fully convolutional neural networks (CFCN) to segment liver and lesions in CT and MRI abdominal images (CFCNs). The CT and MRIs scans were trained using CFCN. This approach uses two FCNs, the Region of Interest (ROI) is produced by the first FCNs, which separate the liver from the abdomen organ. The results are then fed into the second FCN to separate lesions from the ROI in the liver. The method achieved a mean Dice of 93.1% for liver segmentation and 56% for tumor segmentation using the 3DIRCADb dataset.

III. Proposed Approach

In this work, a new method to recognize a human liver organ from an input set of CT images (DICOM), in order to reconstruct a 3D biomechanical model that will be projected later using an Augmented Reality Headset is proposed. For the segmentation process, we opt to implement a deep learning technique residing in an Unet architecture that outputs segmented images of the liver images from a set of volumetric images.

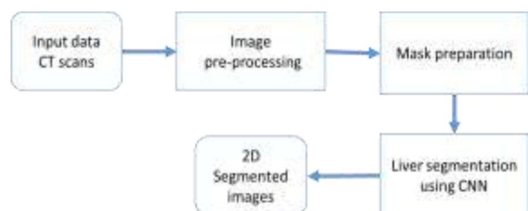

Fig. 1. Liver segmentation approach.

The proposed approach consists of several steps. First, data preprocessing operations are applied to the input set of images which consists of resizing the images and applying the windowing technique with Hounsfield Units measure to recalculate pixel intensity. Then, the mask is extracted from the input dataset and the CNN model is fed with the previous sets of images to obtain segmented images that contain the liver region. U-net was first created and implemented in biological-image segmentation [18].

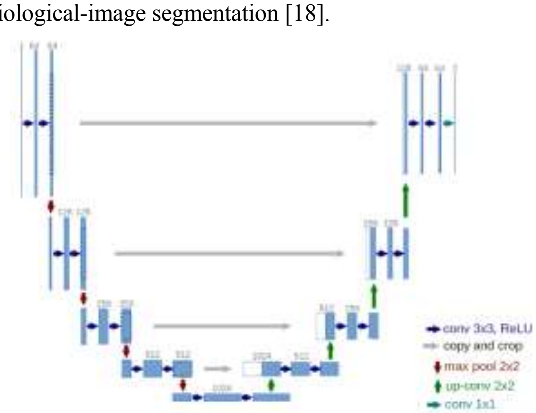

Fig. 2. U-Net Architecture

As described in figure 2, U-net includes a symmetric expanding path that conducts convolution to obtain abstract information and rescales the obtained information to the input data. The output information is the same as the input information. U-net returns a mask that slices the input image. In the case of medical images, each slice is used as 2D input information at each iteration until the full volume is cycled through. Its architecture is composed of an encoder network followed by a decoder network. The encoder network decreases the spatial dimensions in each layer while increasing the channels, while the decoder increases the spatial dimensions and redues the channels.

In figure 2, each blue box corresponds to a multichannel feature map. The number of channels is noted on top of the box. White boxes represent copied feature maps. The different operations are noted in the arrows. The encoder on the left side consists of applying two 3x3 convolutions repeatedly. Each convolution is followed by ReLU and batch normalization. The spatial dimensions are then reduced using a 2x2 max pooling procedure. At each downsampling stage, the number of feature channels is doubled while cutting the spatial dimensions in half. At the decoder side, Every step consists of an upsampling of the feature map followed by a 2x2 transpose convolution, which cuts the number of feature channels in half. Concatenation with the matching feature map from the contracting path is also present, as well as a 3x3 convolutional neural network (each followed by a ReLU activation function). A 1x1 convolution is employed in the final layer to translate the channels to the appropriate number of classes.

A. Dataset Preparation

To evaluate the efficiency of the proposed approach, the 3DIRCADb dataset [3] is used. This dataset is an open dataset. This database contains a different type of liver organ (with a large diversity and complexity of lesions). It is composed of 3D CT scans of 10 women and 10 men CT images from a variety of European hospitals using various CT scanners. In this work, we trained the model using volumetric images (CT scans) of 13 patients. Each patient has a set of 116 slices and each slice has a dimension of 512x512. We used the Nibabel package for converting the input images DICOM format to NIfT format. This plugin gives access to read and write common medical and neuroimaging file formats.

B. Data Pre-processing

Due to memory constraints during training, the dataset is usually downscaled. Slices that did not have any segmentation were cropped to minimize substantial loss of liver information. This guarantees that data segmentation is as dense as feasible after rescaling. After importing and preparing the dataset, preprocessing operations are applied to each slice. To exclude unnecessary organs, a CT windowing technique is used. This technique calculates the pixel intensity measured by the Hounsfield Units (HU), which is a function integrating the radiodensity, u, of a given substance. The HU is calculated using the following equation (1).

$$HU = 1000 \frac{\mu - \mu_{water}}{\mu_{water} - \mu_{air}} \quad (1)$$

The Hounsfield unit values were windowed in the range [35, 350]. The result of the performed preprocessing applied on a raw medical slice is shown in the following figure 3. Before feeding the model with the dataset, the input images were resized (from 512x512 to 256x256) to make the training process more efficient.

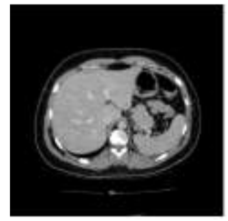

Fig. 3. Enhanced CT Image

The obtained results improve the contrast and the image becomes more detailed. In the right image, the liver region is emphasized and easier to identify compared to the left image.

C. Training and Experimental Settings

The proposed U-net model was trained in Python using Google Colab notebook running on Google's virtual GPU. To define the architecture and layers of the neural network, the model architecture and its layers were defined using TensorFlow and Keras libraries. The model was trained for 20 epochs, which took approximately 1.5 hours per patient. After each epoch, the weights are updated using batch-wise training with a batch size of 10. Dice-coefficient loss function was used along with Adam optimizer to update the weights with a learning rate of 0.0001. Each layer is followed by the Rectified Linear Unit (ReLU) non-linear activation function.

D. Results and Evaluation

For the evaluation of the segmentation approach, we demonstrate the application of the architecture using the IRCADb dataset. After training the model for 20 epochs (49 steps per epoch) on 13 patients with 1508 images in total. We evaluated its robustness by testing it on 7 patients with a total of 812 slices (116 slices per patient). To measure the effectiveness of the developed approach, the Accuracy, the Dice Similarity Coefficient (DSC), and the Intersection over Union (IoU) measures are used.

TABLE I. METRICS OF THE IRCADB DATASET SEGMENTATION

Trained Dataset	**Dice values**	**Accuracy values**	**IoU values**
IRCADb dataset	0.9787	0.9976	0.9586

The model performance looks promising, with a minimum value of 0.95 in the three evaluation metrics. In the following experiments, we tested the model on a set of patients separately for a more consistent evaluation. The results are shown in the following table.

TABLE II. SEGMENTATION METRICS PER PATIENT

Trained Dataset	**Dice values**	**Accuracy values**	**IoU values**
Patient 1	0.9793	0.9977	0.9596
Patient 2	0.9726	0.9969	0.9470

Patient 3	0.9791	0.9976	0.9593
Patient 4	0.9717	0.9967	0.9969

The table highlights the test performance on several patients' data. The robustness of the model is confirmed by the impressive results presented by the Dice, accuracy, and IoU values.

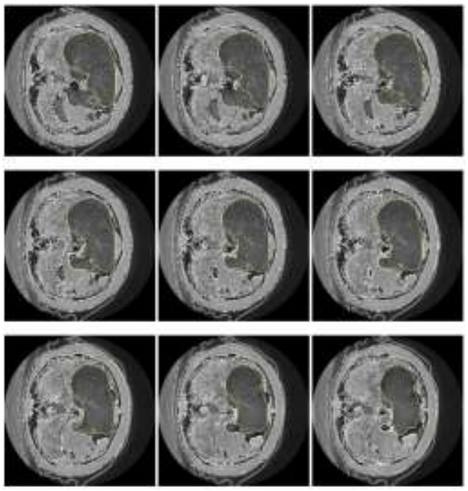

Fig. 4. Set of liver segmented output images of a specific patient

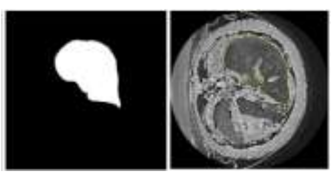

Fig. 5. Result of the segmentation approach: (Left): Liver region mask, (Right) segmented image (output)

The proposed method succeeded in segmenting the liver organ from different patient-specific CT scans. Figure 4 presents a sample of the output images obtained from the proposed model. It can be observed from figure 5, the input raw CT scans, the corresponding liver mask, and the segmented output after the localization of the liver organ. The segmented liver region is contoured in yellow.

IV. Conclusion

In this paper, we presented a method that based on deep learning techniques to perform accurate liver segmentation that will eventually serve to 3D reconstruction of a specific liver model. We used a publically available liver dataset from IRCAD institute as input for the model. The dataset was subject to pre-processing operations to enhance its quality, which consequently results in a better segmentation process. Promising segmentation results were obtained with the implemented Unet architecture, validated by acceptable accuracy values. It will be interesting to integrate a set of Unet architecture that takes axial, coronal, and sagittal types to CT images separately to assure an even more accurate liver segmentation method. As far as the image pre-processing process goes, deeper experiments with noise-reducing methods are planned.

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