
Real-Time Voxel-based 2D to 3D CT Visualisation Framework for Volumetric Capacity Estimation

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Abstract—Over the decades medical analyses have grown in importance and practice possibilities. Digital operations like split-image procedures have become an integral part of modern medical practices and are still gaining momentum. Through the application of this technique medical computed tomography (CT) and magnetic resonance imaging scans (MRI) can be converted to three-dimensional bodies. This paper intends to use these generated objects in a process called segmentation. During this procedure, the desired area gets separated from the rest of the body for analysis and calculation of its physical properties. Furthermore, segmentation can be greatly improved through the utilization of algorithms such as U-Net and K-means or features like augmented reality (AR) or virtual reality (VR). The goal of this paper is to provide doctors with a reliable and simple to use program, which greatly aids in the analysis of patients' data.

Keywords—*voxel-engine; segmentation; machine learning; Kalman-Filter; visualization*

I. INTRODUCTION

Prior to the incipience of the actual segmentation process, the images usually get processed first. The raw CT or MRI scans are often filtered in the frequency domain. These filters remove any unwanted noise and objects from the two-dimensional images or highlight necessary areas, ensuring a higher quality result after segmentation [2].

There are many possible options when it comes to choosing a filtration method, one of which is the “Kalman-Filter”. This specific filter enables interpolation for potentially damaged or erroneous scans [4]. Morphological operations like dilation and erosion highlight the Region of Interest (ROI) areas of a data set while eliminating any undesirable noise. Dilation hereby enlarges the region, whereas erosion downsizes it [5]. After the two-dimensional DICOM (Digital Imaging and Communications in Medicine)

files have been properly processed, the segmentation procedure can commence.

Currently research provides a wide array of options regarding segmentation. For example, Dwivedi Purushart offers a method of segmentation called “threshold segmentation”: Each individual pixel value is compared to a previously specified threshold. This aims to separate the pixels into two groups, one including all pixels with values higher than the threshold and one including all lower values. One of the major upsides of the threshold segmentation technique is its efficiency. Calculation is simple, operation speed is fast and a clear segmentation effect can be obtained if the target and the background have a particularly high contrast. However, the difficulty in obtaining accurate results for image segmentation in areas without significant gray scale difference or with overlapping gray scale values in the image can prove to be disadvantageous. Therefore, threshold segmentation is often combined with other algorithms [6][7].

Another paper from the Department of Radiology, University of Pennsylvania suggests a form of segmentation based on a “simple, learning-free algorithm”, which provides some degree of automation for the process. Consequently, decreasing the complexity of the task and providing faster and higher quality results. A common, semi-automized form of segmentation is the watershed algorithm, which can be visualized in OpenCV [2].

Preexisting methods of segmentation can furthermore be improved upon by utilizing machine learning, making them a potential asset. Implementing machine learning into processes like segmentation and consequently fully automizing them drastically enhances the everyday usability of the software.

This is already a possibility with U-Net, a convolutional neural network (CNN) developed specifically for biomedical image segmentation. In

addition to that, the K-means algorithm can detect groups in unlabeled data sets and is consequently able to segment the relevant data set from the background [1][8][9]. Recently the algorithm saw some usage in analyzing the different mutations of SARS-CoV-2 [10].

Through the application of algorithms such as U-Net or K-means the process of segmentation can be fully automated, streamlining the complexity of the whole process and consequently being able to provide clearer and more precise images or three-dimensional figures than with conventional segmentation algorithms and methods. It currently sees some usage concerning the analysis of MRI and CT scans [11][12][13][14].

Even after a highly optimized segmentation process and the successful creation of a three-dimensional body of the desired object, another important issue is the precise volumetric calculation of the generated object. Despite allowing a more accurate mathematical calculating approach, a complex estimation of the body would still lack in accuracy. Therefore, a simple to use but precise calculation method would benefit radiologists immensely in their day-to-day work and might also influence medical decisions favorably. This could be achieved via a method involving “voxels”. A “voxel” describes the three-dimensional version of a pixel. Like atoms, voxels can create a three-dimensional object by joining together and assembling the desired structure. Each voxel has a predetermined volume, due to its fixed parameters. Additionally, each generated voxel holds a unique density value, which is determined by color, texture and material [15][16]. This concept allows for a program to simply count every voxel within the generated body and through simple addition estimate the size of the segmented object with great accuracy. This is a process which was also employed in the following literature [3].

II. FRAMEWORK

Split-image technology is acting as a cornerstone of many modern medical practices. Utilizing CT or MRI scans, practitioners can more easily identify encapsulated fluids, tumors or other objects and therefore provide an enhanced diagnosis. However, prior to practitioners being able to properly utilize the data, it must be processed first. The modus operandi of our program roughly follows the steps provided in Fig. 1.

Pre-processing happens through morphological operation with a fixed 8 by 8 or 4 by 4 block size like dilation and erosion, while tasks like interpolation and post-processing are taken care of via a linear “Kalman-Filter” with a fixed covariance matrix (Fig. 1, Step 1). The effectiveness of these operations can be seen in Fig. 2. The first image represents the untreated DICOM file, whereas the last scan is the properly processed image ready for segmentation.

Following filtration (Fig. 1, Step 2), the encapsulated fluid or wanted object is segmented from the rest of the image. A range of algorithms is serviceable for segmentation purposes.

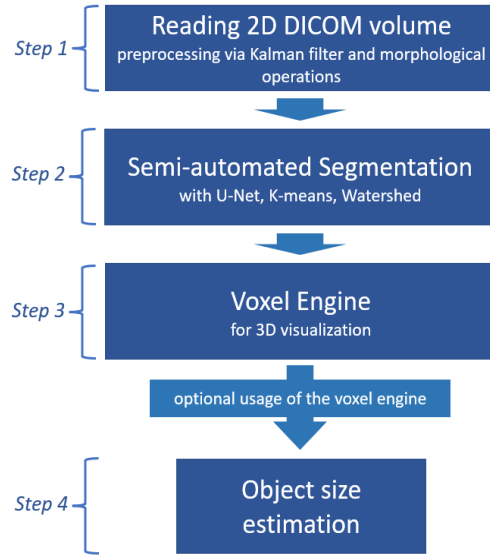


Fig. 1. Voxel-based 2D to 3D segmentation framework



Fig. 2. Effects of K-means segmentation and morphological operations on urinal retention

Converting two-dimensional images into three-dimensional structures, referred to as “3D image visualization”, represents an integral part of segmenting images and is therefore critical for this project. “3D image visualization” describes the process of rendering data of two-dimensional images into a three-dimensional representation. The whole concept of voxel generation is based on an application in Unity 3D in C#. While initially designed for video games, the “Voxel Generator” of the “Voxel Engine” is thoroughly capable of creating a three-dimensional digital structure of organs and tissue. The generated model is composed of many layers of voxels, that are generated using multiple CT or MRI scans as an auxiliary. It is important to understand, that the Voxel Engine can generate a multi-layer structure, because it identifies differences in elevation and position, because it utilizes the x and y positions of each individual pixel and afterwards assigns them their respective z coordinates [17][18][19].

The resolution of the scanned tissue is dependent on the number of voxels used. If the quantity of voxels implemented in the figure is raised, a singular voxel’s size is reduced, which causes the generated model to be more detailed. However, it is critical to understand that an increase in the amount of detail heavily impacts the required memory size, because

more voxels need to be generated for each layer of the object. Due to its flexible nature this method can be employed in many different fields like tumor volumetry for example [18].

Another part of our studies included urinary retention. We applied our framework to multiple cases of urinary retention because we believe that it is an applicable scenario for three-dimensional segmentation and capacity estimation.

Fig. 3 illustrates a case of urinary retention which has been constructed in our Voxel Engine.

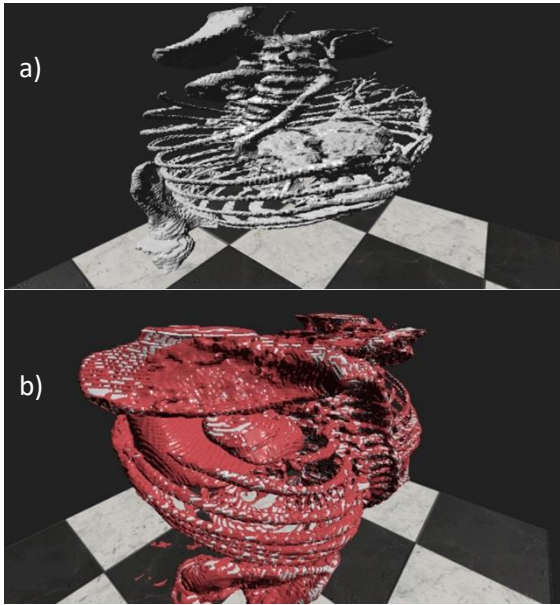


Fig. 3: Three-dimensional representation of urinary retention a) with Kalman filter (grayscale) b) without Kalman filter (red)

Aside from creating three-dimensional objects, voxel-built structures excel at calculating the volume (Fig. 1, Step 4) of certain parts within the structure they assembled comparably to polygons. However, in terms of accurately calculating the objects volume, which is a necessity in the medical field, it is a worse option than voxels. This is due to the multi-layered nature of voxel-built objects. Within in these objects the number of voxels merely needs to be counted within certain parameters, while a polygon-based object is essentially hollow, requiring a much more complicated method of volume calculation, that tends to be more inaccurate than its voxel counterpart. Therefore, this paper utilizes voxel-based volume calculations to determine the volume of tumors, enclosed fluids, parasites etc.

III. EXPERIMENTS

To calibrate the accuracy of the framework two objects were created and scanned via CT and imported into the system to determine their capacity.

Object A is a spherical 3D-printed structure, which was inspired by [20] to additionally calibrate

an MRI scanner. The body itself was created in collaboration with 3D Bee (Austria) utilizing an additive technology which uses synthetic polymer-based resin (duroplast). The object can hold 97.07 ml.

Object B is a cubic 3D-printed body and was produced the same way as Object A. It can hold 19.5 ml.

Both objects can be seen in Fig. 4. The grid inside of them allows for a more accurate calibration process.

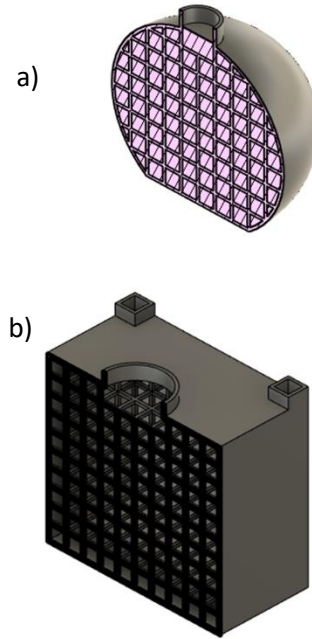


Fig. 4: 3D visualization of object A and B

In table 1 the real as well as the estimated capacity are displayed. The error rate describes by how many percent the estimated capacity varies from the measured one. The units used for the capacity are milliliters (ml)

TABLE I. SIZE ESTIMATION OF OBJECT A, B AND C

Types of Operations	Object	real volume (ml)	estimated volume (ml)	error rate (%)
<i>without morphological operations and without K-means and U-Net</i>	A	97.07	89	8.3%
	B	195	182	6.67%
<i>with morphological operations and without K-means and U-Net</i>	A	97.07	94	3.16%
	B	195	189	3.08%
<i>with Kalman-filter</i>	A	97.07	94	3.16%
	B	195	190	2.56%
<i>with morphological operations and with K-means and U-Net</i>	A	97.07	94	3.16%
	B	195	191	2.05%

IV. CONCLUSION

As shown by the results in table 1 the framework has profited through the mixed usage of voxels, morphological operations and machine learning algorithms. The resulting three-dimensional object and the estimated volumetric size have become more precise. This particularly shows with Object B, which experienced an increase of 4.62% in accuracy while testing the different kind of operations.

Additionally, procedures like interpolation lead to better results, due to their ability to correct erroneous pictures. Furthermore, the results show that machine learning is not only important for the segmentation process but also for the generation of the three-dimensional object.

To keep improving the effectiveness of our system, further testing is required. The data gained through those experiments can greatly aid the quality of our results. This is mainly due to the degree of difficulty when it comes to calculating the capacity of complex bodies.

Even more attention must be paid to the slice spacing, slice thickness and density values of the DICOM images to proceed in future work.

Moreover, the Voxel Engine could be repurposed for various fields besides medical imaging, due to the high flexibility. Furthermore, the visualization aspect works in real time and can always be improved upon which means that the objects can be included in virtual and augmented reality.

As a next step we aim to create three-dimensional models using medical video data to support medical staff in their everyday work. Additionally, the streaming of medical videos for the telemedicine sector is of heightened importance in future work, due to the nature of our framework.

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