Visualization 3D Reconstruction
Volume Rendering of Mucus into Paranasal Sinuses

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Abstract: This position paper explains our method for segmenting and volume rendering in computer tomography images. Our application is developed to reconstruct craniofacial objects in 3D visualization using insight toolkit and visualization toolkit frameworks. We intend to quantify volume rendering of mucus found in CT images and analyze the data which is an important tool in sinus disease treatment. Two algorithms were implemented in order to compare the results: an automatic segmentation and a manual method. Both solutions presented some issues that will be discussing in the next sections.

1 INTRODUCTION

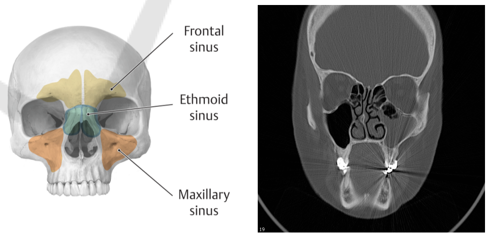
In this position paper, we discuss new solutions to segment and visualize 3D Computer Tomography (CT) images.

Computer Vision (CV) is an important tool to Medical Diagnosis, with emphasis on segmentation and image processing (Szeliski, 2011). Visualization, in CV is a transformation of data or information in pictures. Two open-sources software help us to work with visualization. Visualization Toolkit (vtk) is a C++ class library that supports volumetric methods and advanced modeling techniques while Insight Toolkit (itk) is a medical library that implement image processing algorithms and segmentation tools(Schroeder et al., 2002).

We applied visualization in craniofacial CT images and demonstrated how works segmentation and visualization adopting vtk.

Computer tomography has a long history starting with a X-Ray discovered in 1895, by Wilhelm Conrad Röntgen (1845-1923). Allen MacLeod Cormack (1924-1998) and Sir Godfrey Hounsfield (1919-2004) were pioneers of medical computer tomography (Buzug, 2008). Sir Godfrey Hounsfield also transformed attenuation values, normally represented in gray values, onto a dimensionless scale and related to attenuation value of water. These values is a quantitative scale for describing radiodensity (Buzug, 2008).

Craniofacial CT, Figure 1, can illustrate where is the region of interest and where mucus accumulates in paranasal sinus.



(a) (b)

Figure 1: Paranasal air sinuses (Gilroy et al., 2012).

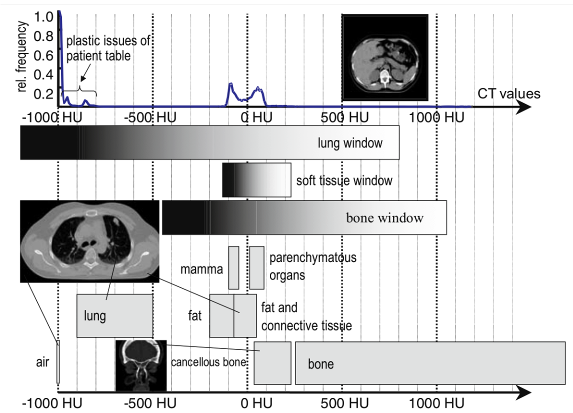


Figure 2: Hounsfield Units (Buzug, 2008, p. 477).

Figure 2 illustrates common HU of body human. On CT images, the mucoid attenuation HU is simi-

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lar to or less than paraspinal skeletal muscle, +10 to +40 (Agarwal et al., 2010). According to Cummings Otolaryngology, two cases need to be analyzed; when sinus secretions are acute and of low viscosity, the HU range is from +10 to +25; In chronic state, sinus secretions become thickened and concentrated and the HU range have density measurements of +30 to +60 Hounsfield units (Flint et al., 2010).

Drebin, Carpenter and Hanrahan, 1988, proposed that these values could be used to classify volume in CT images. They used transfers functions for this classification. Transfer function can map information at a voxel location into different values such as material, color and opacity. Levoy, 1988, created a new method, adding a gradient magnitude dimension to the specification of a transfer function because classify a volume just based on scalar value was not capable of isolating an object (Drebin et al., 1988; Levoy, 1988; Schroeder et al., 2002).

Levoy, 1988, found several problems when the image has slight changes in opacity ramps or when interpolation methods radically alter image features. Totsuka and Levoy, 1993, proposed a new volume rendering method that works in frequency domain, differently from conventional methods that works in spacial domain. This method results less reality images because do not shows occlusion.

This paper proposes a new application and a mix of techniques that can segment and visualize small ranges of HU index. The itk library is used to process and segment, while vtk renders and quantify accumulated mucus.

2 RELATED WORK

Silva, 2008, described an active shape method (asm) to finding and segmenting mucus in computer tomography images, however he has not implemented Hounsfield values and 3D reconstruct.

Zhang, 2012, combined a sub-block Otsu Algorithm, and image enhancement, with anisotropic diffusion filters to improving contrast and protect edges (Zhang et al., 2012). This process is explained in Figure 3.

We intend to use local optimal threshold segmentation (Zhang et al., 2012) to resolving the same subject that Silva (2008) was working.

Yan et al., 2012, proposed reconstruct the gastrointestinal tract in three dimension adopting a CR or MRI images. They used Matlab for image registration, photoshop to perform the segmentation and the vtk to reconstruct and visualization.

Figure 4 shows an image registration process

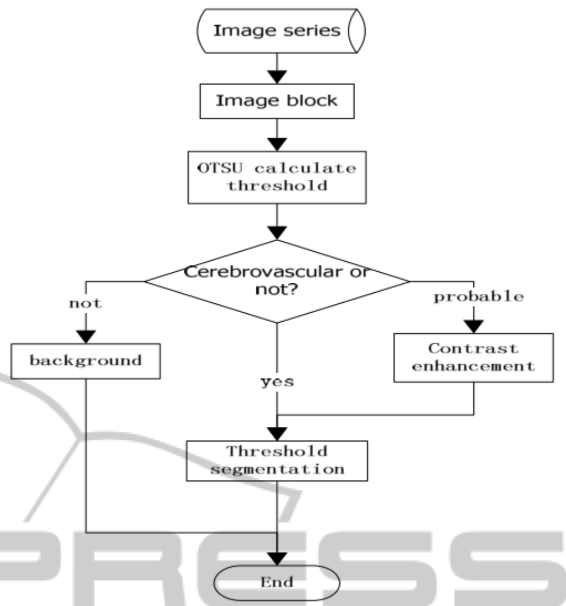


Figure 3: The process of image segmentation (Zhang et al., 2012).

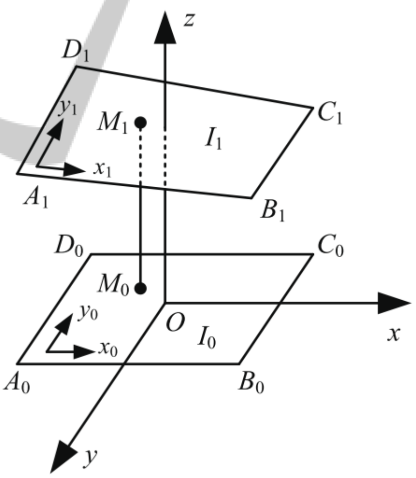


Figure 4: Image Registration (Yan et al., 2012, p. 24).

where I_0 is the reference while I_1 is the image to be registered. Then, the method creates a relationship between any point $M_1(x_1, y_1, z_1)$ in the point I_1 and the point $M_0(x_0, y_0, z_0)$ at the identical position in the I_0.

Wang et al., 2014 improved the Marching Cubes (MC) algorithm. This method is fundamental for classification volume process and is a widely routine used to extract isosurfaces from volumetric data set. The MC technique divides volume data set into cells and then create triangles to approximate isosurfaces within each cells.

Standard MC method generates the type A ”hole problem” which occurs when at least one cube face has an intersection point in each of its four edges. The type A happens because the MC process each cell sequentially without considering the neighboring cells of an active cell. This method requires each cell to be visited at least once to ensuring its activeness property.

Wang et al., 2014, proposed to use Adjacent Lookup Table (A-LUT) to improving performance. A-LUT method is used to guide which cells to visit from a given cell. MC and A-LUT method together can segment more efficiently and fast than standard MC. Also this technique detects more objects because AlutMC can find limits between different isosurfaces.

3 METHOD

Our method is implemented in C++ using itk 4.7 and vtk 6.1. The project was created using object oriented programming benefits. Itk and vtk are a freely open-source software, the first is for image processing and registration and the second for 3D graphics and visualization. Both library works with Digital Imaging and Communications in Medicine (DICOM) and we can link these frameworks making a conversion between platforms.

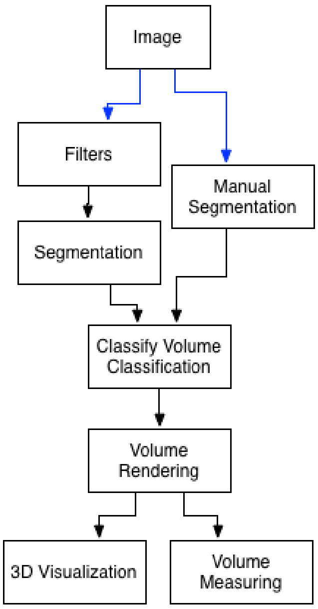


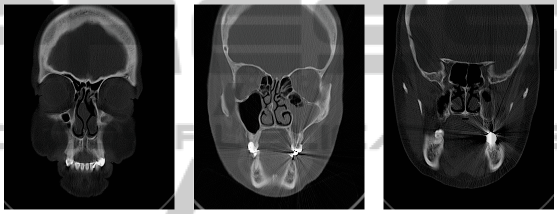
Figure 5: Our method.

In this position paper, we use DICOM images from Silva, 2008, qualification work. Silva analyze seven dataset DICOM series from different people. Two different segmentation techniques were implemented; one automatic, with image processing before segment and other manual, just to compare results with automatic segmentation. Figure 5 show all steps from our solution.

3.1 Manual Segmentation

Manual Segmentation uses same DICOM images as automatic process. This DICOM serie has 34 images, but maxillary sinus appear from 12 to 26.

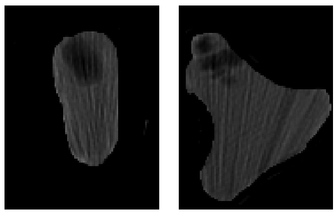
Figure 6(a) and 6(c) shows the start and finish images in this process. It is important to know that this sequence is not generic and results can be compared just if the automatic process use the same DICOM sequence. This process is just a method to compare both results.



(a) 12 (b) 19 (c) 26

Figure 6: DICOM image sequence.

Figure 6(b) shows left maxillary sinus with an inflammatory process. MIPAV medical software for educational purpose was used to cut the region of interest as the Figure 7 illustrates.



(a) (b)

Figure 7: Manual maxillary sinus segmentation.

The volume will be segmented and results will be used to compare with automatic process. We can see all process in Figure 5.

3.2 Image Processing and Segmentation

This process is necessary to image enhancement. Filters can remove noise to improving results in segmentation process. Silva, 2008, used in his work median filters and high pass filters to removing almost noises (SILVA, ROBSON LUÍS, 2008).

Vtk has some class, see Section 3.3, that can filter, segment and render the surface. The vtk classification method uses a Marching Cubes (MC) technique to filtering surfaces that represent a constant valued scalar function. MC method, implemented in vtk, resulted an unsuccessful segmentation on small ranges in Hounsfield Index. Itk will be used to filtering and to segmenting before starting volume rendering in vtk library (Schroeder et al., 2002).

The itk library has algorithms that can classify the volume of the object with Hounsfield Units, like vtk, but before, the itk library will be used to reduce noise and prepare image for segmentation and visualization. Noises with high density materials, like metal artifacts in dental fillings, generates a noise in CT images that need to be solved before image segmentation. Figure 8 show this problem.

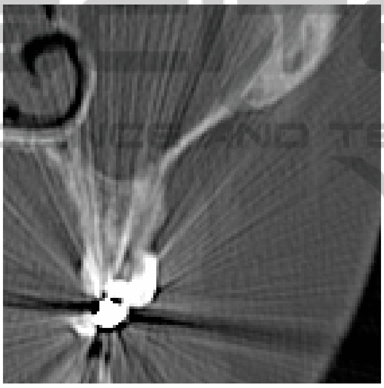


Figure 8: Metal artifacts in CT image.

Metal artifacts reduction (MAR) methods can remove this noise. Wang et al., 2013, proposed a new method, FP-MAR, that consists of an interpolation method with an edge-preserving blur filter (Wang et al., 2013). This process needs to be as efficient as possible for a good segmentation then be done.

Itk and vtk have good methods to segmenting CT images. One of them is the Threshold method that can cut a region of interest using a normalized HU range or value.

3.3 3D Volume Rendering

Previous results, like image processing and segmentation techniques, have a big importance for this process. Images with metal artifacts or other types of noise need special and effective filters. Vtk is the main tool for this process. In reconstruction process, we use from the output segmentation process information which consist in a vtk data type, more precisely, image data.

Three important algorithms for volume rendering will be tested, *vtkMarchingCubes*, *vtkContourFilter* and *vtkContourFilter* with *vtkPolyDataNormals*. VtkMarchingCubes is a specific class to generating volume data and this class use an image data with dataset type. Other two algorithms are generally used for generics operations. Generality, generics operations have more cost in a CPU times and specialization in programmer time (Schroeder et al., 2002).

VtkMarchingCubes implements MC technique and is more efficient than other two methods because it can render the volume with more resolution and precision and works with the same dataset type that DICOM images (Schroeder et al., 2002).

3.4 Volume Measuring

After volume rendering we need measure how much mucus has in this selected volume. Vtk provides algorithm called *vtkMassProperties* to do this, based in Alyassin A. M. et al., Evaluation of new algorithms for the interactive measurement of surface area and volume, 1994 (Kitware Inc., 2014).

In Alyassin A. M. et al., 1994, paper, they analise two different techniques for open and close planes, one for volume other for surface area. For this paper, the volume measurements technique in close planes, MUNC (Maximum Unit Normal Component) and DTA (Divergence Theorem Algorithm), is essential to finalize the entire process.

The MUNC algorithm calculates normal vectors components from pointlist using the gradient of the image function *f(x,y,z)* at the marked surface points. The magnitude of the normal vector for each point in the pointlist normalize the gradient. The surface area is estimated using voxel counting to sum marked voxels (Alyassin et al., 1994).

The Δa_i is the differential surface area and is calculated as,

$$\Delta a_i = \begin{cases} \frac{\Delta x \Delta y}{|n_{z_i}|}, & \text{if } n_z \text{ is the MUNC} \\ \frac{\Delta x \Delta z}{|n_{y_i}|}, & \text{if } n_y \text{ is the MUNC} \\ \frac{\Delta y \Delta z}{|n_{x_i}|}, & \text{if } n_x \text{ is the MUNC,} \end{cases} \tag{1}$$

where Δz, Δy and Δx are dimensions and n_x, n_y and n_z are the unit normal vector components. If $\Delta z = \Delta y = \Delta x = 1$, then we can reduce the differential area to the reciprocal of the absolute value of the MUNC. In this case, surface area is calculated as,

$$\text{surface area} = \sum_i^n \Delta a_i = \sum_i^n \frac{1}{|MUNC_i|}. \tag{2}$$

The DTA estimates the volume of an object, from its pointlist and the following equation estimated the volume.

$$volume = k_x \sum_i (x_i n_{x_i} \Delta a_i) + k_y \sum_i (y_i n_{y_i} \Delta a_i) + k_z \sum_i (z_i n_{z_i} \Delta a_i), \quad (3)$$

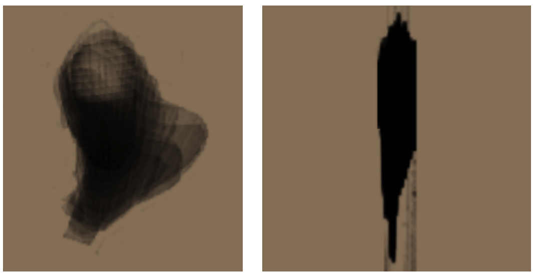
Where Δa_i is defined by Equation 1; x, y and z are coordinates; k_x, k_y and k_z are coefficients whose sum is equal 1 and are defined as the fraction of the total number of points in which the MUNC of those points' gradient vector was in the direction indicated by the subscript coefficient. DTA method requires a smooth and closed surface (Alyassin et al., 1994).

More details about MUNC and DTA methods(open and close), refer Alyassin et al., 1994.

4 EXPERIMENTAL RESULTS

Initially, we wanted to segment mucus in paranasal air sinus adopting a simple vtk process and using a Hounsfield Unit (HU). Until now we can not resolve this problem, because vtk process can not segment small HU ranges.

Manual segmentation was implemented to comparing precision in automatic process. Figure 9 illustrate these results.



(a) (b)

Figure 9: Manual segmentation reconstructed.

Current manual segmentation method fails when tries three-dimensional reconstruct, Figure 9(b). After cut and convert original DICOM in PNG segmented image the object loses dimensional and slice distance values and results bidimensional image. After insert slice and dimensional values, the results are improved but the three-dimensional image not ilustrate real volume.

Improvements in manual segmentation are being performed. We are testing this process without PNG conversion, using region of interests cut algorithm implemented in itk library to segmenting without convert format.

Automatic process results a successful segmentation according to Figure 10 shows. Classify surfaces

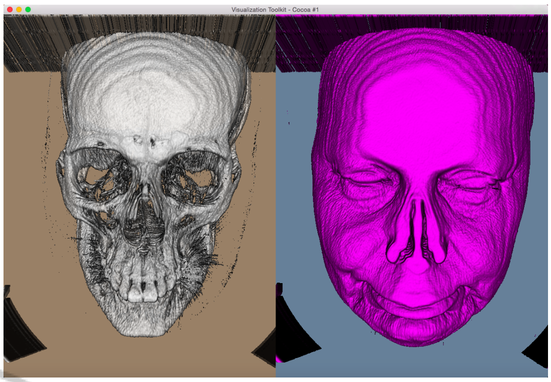
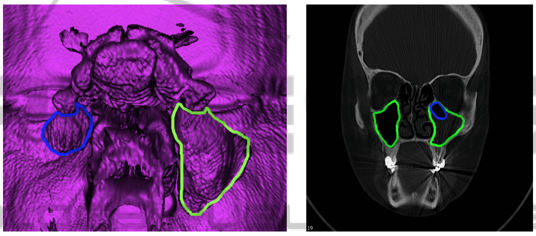


Figure 10: Volume rendering with vtkMarchingCubes.



(a) (b)

Figure 11: Maxillary sinus rendered (a) and detached maxillary sinus on CT image (b).

using HU values have some problems when the values are similar or are part of the same window, like soft tissue (-125 to +225) and mucus (+10 to + 40).

Has been shown in Figure 11(a), the right maxillary sinus (on the left after rotation), green contour, is bigger than left maxillary sinus in blue contour, because this process until now can not render the mucus volume and just render air spaces as the Figure 11(b) shown.

5 CONCLUSIONS

Classify and visualize the volume of the object using vtk proved be a simple process when the goal is surfaces like bone or all soft tissues together. This work is researching a method more accurate to extract a small HU range. Until now, filters and independent segmentation method to improving the objective help but not solved all the problems.

Conversion between itk and vtk worked fine. In Manual process, the conversion of segmented image in PNG lost all DICOM information and even if dimensional and slices values are inserted, the method can not render as we expected.

We can not compare Manual and Automatic process until we solve the problems in our algorithm, then we do not have measurement results with both process.

Has been shown in Figure 11, the process can not render mucus volume. We need improve our methods and research in others bibliographies about HU for sinus inflammatory process.

The next steps will be experimented new methods and implemented more tests with this algorithms and others, like Silva, 2008, with active shape models, but considering hounsfield units.

New DICOM image series without metal artifacts noise will be added to compare results and Wang et al., 2013, techniques will be implemented to resolving metal artifacts noises.

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