Vascular structures extraction by background normalization

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Abstract: *The vessel structures of the blood circulatory system are one of the most complex structures of the human body. Modern computed tomography techniques allow acquiring high resolution images, but at the same time, the amount of artifacts in output images is quite high. They may affect diagnostic result and may obscure or simulate pathology. The idea of our method represent a 3D computed tomography image a combination of vascular structure and background that has normal distribution in some neighborhood. The proposed approach can be applied to denoising computed tomography images, enhancing of contrast in lesion areas without changing topology of initial vessel structures. Experimental results show that it can archive non-uniform luminocity and contrast normalization*

***Keywords*:** computed tomography, background normalization, vascular structures.

1. INTRODUCTION

Vascular diseases are among the most important health problems nowadays. Diseases of the circulatory system are more than a half of all death causes in Belarus in 2015 [1]. This fact justifies research efforts that provide better understanding of the vascular system structure as well as related processes and diseases.

It is essential to clearly detect vessel structures present in the image. In the recent years, a vast variety of algorithms and methods of vessel extraction appeared [2]. The approaches differ in the assumptions made about the shape and structure of physical vessels [3], the medical imaging modalities, the mathematical models describing the vessels, the image features used to detect them, and the algorithmic schemes to extract them [4].

Computed tomography (CT) images are crucial diagnosis basis to gather clinical information. With high radiation dose, monochromatic X-rays, infinite detector resolution, perfect detectors, no scatter, and no motion, CT images would be a perfect reflection of reality. If any of those conditions are not met, then artifacts will occur.

There are many different types of CT artifacts, including noise, beam hardening, motion, scatter, metal artifacts, etc. And it has been introduced different techniques for reducing influence of each kind of artifacts [5]. However, after applying these techniques, areas with non-uniform local luminocity and contrast drift remain.

The main idea of our approach is to represent a CT image as a combination of vascular structure and background that has normal distribution in some neighborhood of this structure. Many features in CT images should be more visible by background normalization process. Locally adaptive non- linear filters decrease global difference between bright and dark voxels, even if it produces better local contrast. Here we propose a new method based on model of observed image for normalizing for both luminosity and contrast. Luminosity and contrast shifts are observed from background part of the image and are used for normalization of whole image. Even if this method is used for CT images, this can be used to any non-uniformly illuminated image.

2. BACKGROUND NORMALIZATION

The cardiac computed tomography images were used; every layer had 512x512 pixels, from 200 to 360 layers per one volume data.

2.1 Background definition

Resulted image can be regarded as transformation on the original one:

$$I_r = F(I_o) = F(I_f + I_b), \tag{1}$$

where I_r – resulted image, I_o – original image, I_f and I_b – foreground and background of original image, respectively; F represents acquisition transformation function.

We assume that resulted image is a linear combination of original image and contrast shift and luminosity:

$$I_r(x,y,z) = C(x,y,z) * I_o(x,y,z) + L(x,y,z), \tag{2}$$

$$I_o(x,y,z) = \frac{I_r(x,y,z) - L(x,y,z)}{C(x,y,z)}, \tag{3}$$

The recovery estimation of original image I_o is based on estimation of C and L.

It is quite difficult to predict all the properties of I_f, but I_f can be statically modeled as normal distribution:

$$I_b(x,y,z) \sim N(\mu_b, \sigma_b), \tag{4}$$

where μ_b is mean value and σ_b is standard deviation representing natural variability in some neighborhood of (x,y,z) voxel.

Using above model of I_b and it's further simplification, background voxel can be represented as:

$$I_b(x,y,z) \sim N(L(x,y,z), C(x,y,z)) \tag{5}$$

2.2 Artifact processing

To extract the background image I_b, we did the following assumptions:

1. All background voxels should have different value than foreground voxel for every voxel in some neighborhood for this voxel.
2. There are at least 50% background voxels in this neighborhood.

3. Both C and L are constant functions.

The first assumption states that voxels belong to background or not can be determine simply by examining their intensity. For each voxel (x, y, z) in the image, mean, $\mu_N(x, y, z)$ and standard deviation $\sigma_N(x, y, z)$ of intensities in neighborhood N are estimated. Estimator $\hat{\mu}_N(x, y, z)$ is used as sample mean and estimator $\hat{\sigma}_N(x, y, z)$ is used as sample standard deviation. Voxel (x, y, z) is said to be background voxel if its intensity is closed to mean intensity. The background image can be achieved according to Mahalanobis distance from (x, y, z) to $\hat{\mu}_N(x, y, z)$:

$$dist_M = \left| \frac{I(x, y, z) - \hat{\mu}_N(x, y, z)}{\hat{\sigma}_N(x, y, z)} \right|, \qquad (6)$$

If $dist_M$ is lower than threshold, then (x, y, z) belongs to background.

The second on indicates that sufficient background area must be present in each N The third assumption is based on the fact, that C and L are concentrated in the low frequencies.

2.3 Contrast and lumocity shift estimation

Given the background set I_b, $L(x, y, z)$ and $C(x, y, z)$ can be derived for a voxel. From (4) and under the first assumption background voxel intensities in each neighborhood are independent, identically distributed random variables. $L(x, y, z)$ and $C(x, y, z)$ could be calculated for each voxel by estimating mean value and standard deviation of this distribution in N.

This approach requires a lot of computational efforts. In addition, we have sparse set of voxels which make filtering more difficult. Therefore, we split input layers on set of squared sub-images S_i. From the background set I_b in S_i mean and standard deviation is estimated. Full luminosity and contrast drift were then obtained by applying bi-cubic interpolation on the sub-sampled images.

Neighborhood size to calculations was chosen empirically, it depend on thickness of vascular structures and can be found by the following formula:

$$N(p) = \bigcup_{|v-p|<10*M_T} v, \qquad (7)$$

where $p \in R^3$ – considered voxel, $|v - p|$ – Manhattan distance between v and p, M_T – maximum thickness of vessels on a layer. Constant 10 was chosen empirically. It leads to accounting all local artifacts around an object and doesn't include artifacts of other objects. An example of a layer is shown on Fig.1, estimated luminocity and contrast shifts are in Fig. 2.

2.4 Background normalization

As we have grayscale image, normalization can be performed with the following procedure:

$$I_o(x, y, z) = \frac{I(x, y, z) - L(x, y, z)}{C(x, y, z)}, \qquad (8)$$

Fig.1 – The one original layer of source 3D medical image.

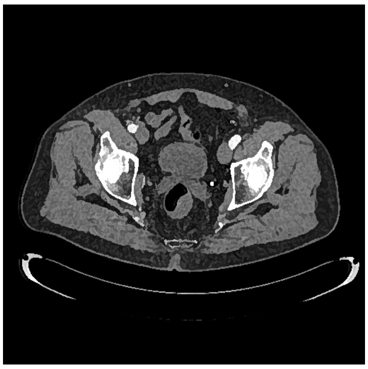
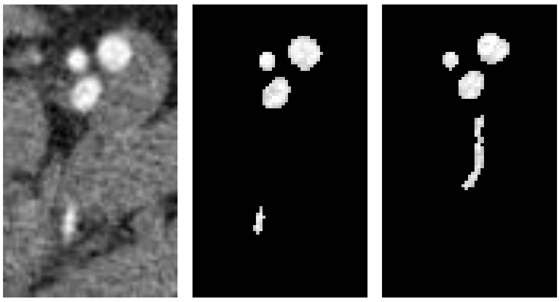


Fig.2 – The layer after correction luminocity and contrast shift.

3. SKELETON EXTRACTION

After normalization of each layer, reconstruction algorithm applied.

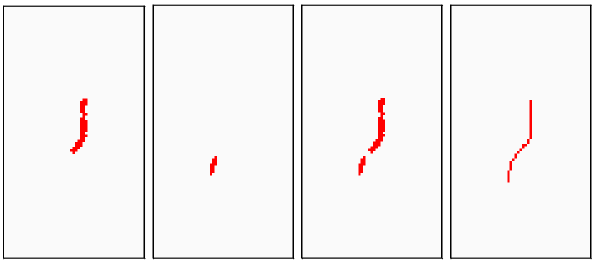
Source data of this part of algorithm are binary layers that were created after segmentation. Objects on this layer can have any position and for one 3D object regions on image may not have connection. The basic trouble of skeleton extraction is definition connection of such region (Fig.3).



a) b) c)

Fig.3 – Fragment with uncrossed objects: a) source image; b) first binary layer; c) second binary layer.

The first algorithm step is the selection of crossed objects between layers and removing them from images. It is realized by conjunction that allows defining crossed regions. After this, center mass of every region is calculated. Using these coordinates, we can remove crossed regions from duplicates of source binary images. Resulting images from adjacent layers are combined by disjunction. On this stage it is necessary define maximal distance where objects can be connected (Fig. 4). Dilatation for half of this distance connects these separate objects. Euclidean thinning helps to define lines for interlayer object correction. It is possible to use this line for generation new binary image for intermediate layer to connect regions into the object.



a) b) c) d)

Fig.4 – Connection of uncrossed objects: a) first object; b) second object; c) two object on image; d) line for connection.

These lines are used in algorithm for intermediate layer reconstruction for connection of center of mass (Fig. 5) that was described at [7].

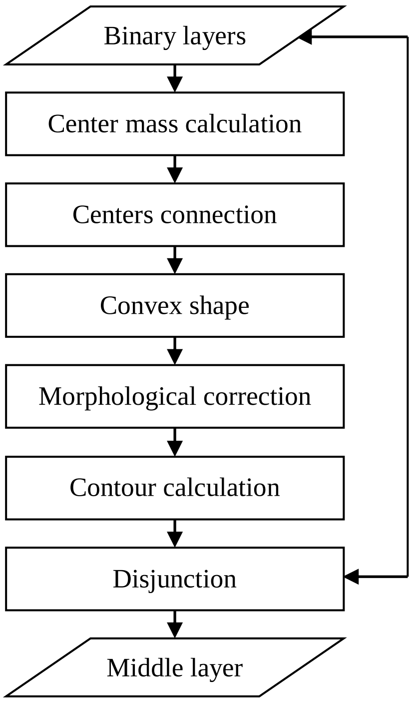


Fig. 5 – Region construction algorithm.

The trouble is definition regions for distance map construction in 3D space. On united layers image it possible to have as crossed as no crossed image. A measurement of image objects for hole existence allows to remove all objects with hole.

Contour definition regions are constructed by connection neighboring object by convex shape.

Then distances between center of mass analyzed for all no crossed objects. Pair of objects is formed on base of this information. For every pair of object convex shape is calculated. A border this convex shape is corrected by watershed line of previous level. Consolidation of corrected convex contour and objects allow to define regions for contour detection.

Disjunction of results of processing connected and no connected objects allows to determine intermediate contour objects by watershed. Similarly, detected objects contour for other intermediate levels.

The intermediate layers construction can be realized by analysis of distance map properties [6]. Rides of distance map correspond to contours of optimal intermediate layer. In addition, they correspond to watershed lines. Taking in consideration aforesaid, we used technique [7] in order to reconstruct 3D object surface from several closed, in general, non-planar curves. Before that we applied dilatation to constructed skeleton. Detailed description of algorithm can found at [7], results are shown on Fig. 6.

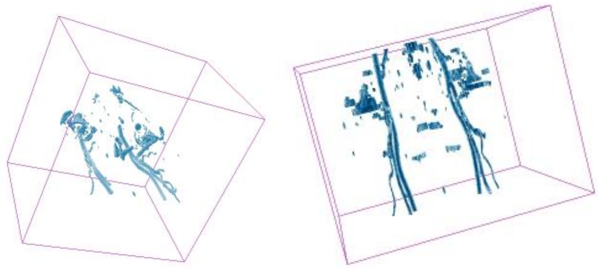


Fig. 6 – Reconstruction of 3D object by intermediate layer generation.

The result of such reconstruction includes many noisy objects.

False objects are removed by scrap function that is based on 3D connected component analysis. The algorithm starts processing from line analysis. For digital images, there are a few ways to calculate the geometric characteristics. The image voxel has linear dimensions. However, calculation of geometric characteristics is performed on base of definition of corner points of object shape. In this case, point size corresponds to real size. The third coordinates (z) of the geometrical position of the line is defined as coordinate pair for left and right point in line. However, with such characteristics stack difficult to organize. Basic iteration for object analysis is going by z. Then effectively organization of additional structure information, that is necessary to monitor through the motion by the axis. During analysis of connected component, initial basic characteristics are calculated: volume, surface area, geometric spatial points, brightness and color. They are determined by the accumulation of the scan lines. Volume is the sum of the lengths of all lines and surface area. After definition of 3D object characteristics small objects are removed (Fig.7). Result of operation consists of vascular structures, but we can improve it by removing short vessels and fibers. Using algorithm for 3D thinning [8] we can calculate length of every structure and remove shortest of them. Dilatation allows to us reconstruct vascular structures.

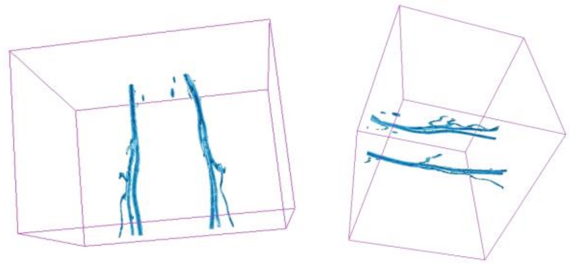


Fig. 7 – Filtered objects after 3D reconstruction.

4. CONCLUSION

The proposed method consists of two parts: background normalization and vascular structures reconstruction.

The first part achieves non-uniformly luminosity and contrast normalization of CT image. It enhances the contrast of areas without changing the characteristic of original physiological structure, what is essential on the second step.

The second part allows to obtain high quality results due to the recovery of intermediate sections. Using objects' merging on the intermediate layer ensures the stability of the algorithm for objects of any shape. The actual path between the layers can be efficiently determined by distance maps and as well as original geometrical object properties preserved.

The algorithm was tested on images with complex medical objects. It demonstrated good results for all cases. Compared to analogs, the proposed algorithm is self-contained – it works with raster layered images without additional transformations.

5. REFERENCES

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