

INTRODUCTION

Automatic segmentation of human anatomical structures is a challenging problem in medical images analysis. At the state of the art some semiautomatic and few automatic procedures have been developed, based on different techniques as threshold, clusters, deformable models and probabilistic methods [1]. Depending on the acquisition technique and on the anatomical structure, these methods offer different results. In MRI, manual, semiautomatic or automatic software have been developed for brain segmentation in the research sector [1]. Automatic software have been developed for bone segmentation in CT, while semi-automatic or multi-scans algorithms have been developed for heart and vessels segmentation in CTA [2]. We describe a robust automatic method for the deterministic identification and segmentation of anatomical structures in medical 3D images. The method is based on the modelling and the analysis of anatomical structures physical and geometrical features. The method is characterized by high precision and use of non subjective parameters.

METHODS

We analyzed data of single anatomical structures, including the brain, white matter, grey matter and skull, in a database of 250 MRI scans of the head [4]. We then analyzed data of single anatomical structures, including the bone, the heart, the aorta, urinary tracts, bladder and kidneys, in a public database of CT and MRI (<http://pubimage.hcupe.ch:8080/Obelix>). We used mathematical models to perform analysis of the tissues intensity distributions. Physical and geometrical properties of the systems determine intensity distributions. Therefore they can be modelled as the combination of a function describing the random variability of the tissue detection intensity and a function describing its geometrical properties. Assuming that the problem is characterized by spherical symmetry, the function describing the tissues intensity distribution is:

$$Eq.1: D_{3D}(I) = \sum_{i=1}^{n_t} A_i e^{-\left(\frac{I-C_i}{2\sigma_i}\right)^2} \cdot 2\pi^2 (\bar{r}_i(I))^2$$

3D: 3-dimensional; I: Intensity; t=Tissue; n_t = Number of tissues;
C: Gaussian centroid; A: Gaussian height; $\sigma \equiv FWHM/2.35$;
 $\bar{r}_i(I)$: Geometry dependance function

The segmentation algorithm is the evolution of the algorithm presented at 15th ISMRM-ESMRMB Annual Meeting 2007. It is based on automatic landmarks localization, iterative intensity analysis, threshold, morphologic operators and features analysis [4]. The algorithm consists of the subsequent automatic steps: 1.Global Intensity Analysis. 2.Landmarks Localization. 3.Morphologic Operators Application and Features Analysis. 4.Local Intensity Analyses. The 4th steps is performed on volumes that include the external surfaces of the structures (Fig.1). This step evaluates tissues local intensity independently from local magnetic field effects and tissues alterations.

RESULTS

The implementation of the algorithm for encephalon, grey and white matter segmentation (Fig.2) was tested on 215 different subjects scans. The efficiency is 93% for automatic landmarks localization [4]. The first estimate error for the cerebral volumes is 4.5%, vs 8-9% [3] state of the art errors. The algorithm have been semi-automatically applied on body CTA to segment bone and tissues supplied by contrast medium, characterized by very similar intensities. The results showed easy and excellent segmentation of heart, aorta, urinary tracts, bladder and kidneys (Fig.3).

DISCUSSION

The comparison of the first estimate volume error of our algorithm (4.5%) vs state of the art volume error in MRI brain segmentation (8-9%, [3]) enhances the algorithm precision improvement. The bone-vessels segmentation results on the CTA of the body express an achievement that have not been described yet in literature. This fact enhances again the efficiency of our algorithm, and its great adaptability properties. Moreover, the segmentation of these structures one from each other can be easily implemented. The deterministic approach of the algorithm, the fact that it's based on modelling and mathematical analysis of the geometrical and physical properties of the structures, is also an important achievement in segmentation. In fact, although segmentation methods have been developed, low results concordance is evident at the actual state of the art, because the algorithms are not justified through physical criteria. Further segmentation tests will be done on MRI and MRI angiography on various anatomical structures.

REFERENCES

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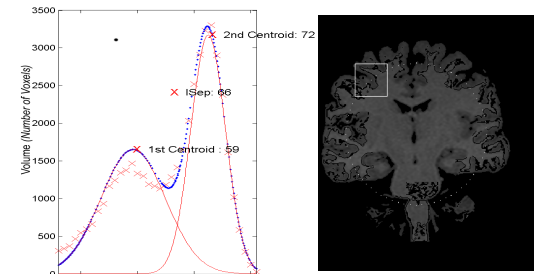


Fig.1: Local intensity analysis on a peripheral volume. Right: Coronal view of the segmented brain. White square: middle section of the local analysis volume. Left: Local Intensity Distribution (Red x), Sum of two Gaussians fit (Blue Dots), Single Gaussians (Red Lines).

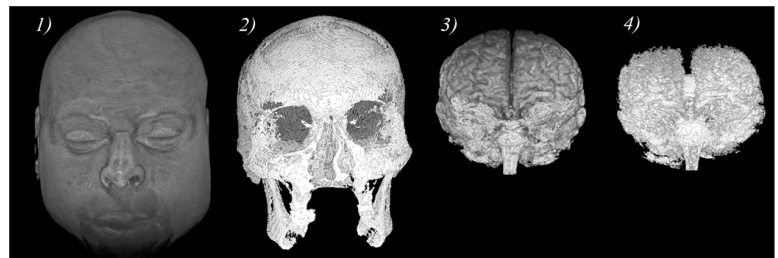


Fig.2: 3D reconstruction of the results from the application of the realized algorithm on MRI scan of the head: 1) Head; 2) Skull segmentation; 3) Encephalon segmentation; 4) White Matter Segmentation

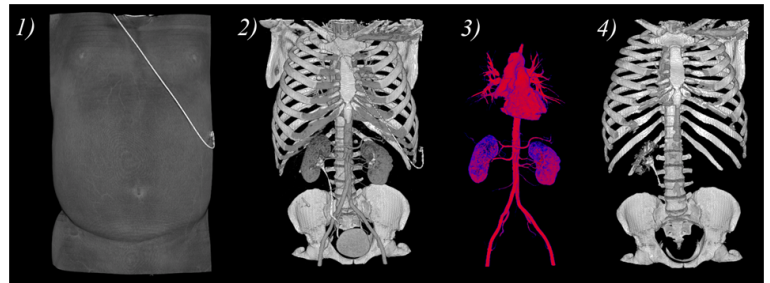


Fig.3: 3D reconstruction of the results from the application of the realized algorithm on CTA scan of the body: 1) Body; 2) Bone and Circulatory System segmentation; 3) Circulatory System and kidneys segmentation; 4) Bone Segmentation