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Genus zero graph segmentation: Estimation of intracranial volume ☆

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ABSTRACT

The intracranial volume (ICV) in children with premature fusion of one or more sutures in the calvaria is of interest due to the risk of increased intracranial pressure. Challenges for automatic estimation of ICV include holes in the skull e.g. the foramen magnum and fontanelles. In this paper, we present a fully automatic 3D graph-based method for segmentation of the ICV in non-contrast CT scans. We reformulate the ICV segmentation problem as an optimal genus 0 segmentation problem in a volumetric graph. The graph is the result of a volumetric spherical subsampling. The equidistantly sampled data points are connected using Delaunay tetrahedralisation creating a highly connected neighborhood. A Markov Random Field (MRF) is constructed on the graph with probabilities learned from an Expectation Maximisation algorithm matching a Mixture of Gaussians to the data. The result of the MRF segmentation is compared to manual segmentations performed by an expert. We have achieved very high Dice scores ranging from 98.14% to 99.00%, while volume deviation from the manual segmentation ranges from 0.7% to 3.7%. The Hausdorff distance, which shows the maximum error from automatic to manual segmentation, ranges from 4.73 to 9.81 mm. Since this is sensitive to single error, we have also found the 95% Hausdorff distance, which ranges from 1.10 to 3.65 mm. The segmentation is very consistent with the reference and differs only in difficult areas, where it seems that our method is much more slice-wise consistent than a manual segmentation. The proposed method is expected to perform well for other volumetric segmentations.

1. Introduction

Unicoronal synostosis (UCS) is a congenital craniofacial malformation characterized by the premature fusion of one of the coronal sutures, potentially leading to asymmetric head shape, craniofacial growth disturbances, increased intracranial pressure and developmental delays. Computed Tomography (CT) scanning is usually performed to confirm the diagnosis and to facilitate surgical treatment planning. The intracranial volume (ICV) in children with premature fusion of one or more sutures in the calvaria may become reduced, leading to risk of increased intracranial pressure [1]. Challenges for automatic estimation of ICV include holes in the skull in newborns (the fontanelles), but also holes in the cranial base (e.g. the foramen magnum and other foramina, fissures and synchondroses).

The main contribution of our work is a fast and fully automatic method for segmentation and estimation of the ICV in CT scans of children with craniosynostosis. The method is based on the construction of a volumetric graph description of the skull volume. The graph has equidistantly spaced sample point connected via tetrahedralisation. The clamping of special nodes consistently produces graph cut segmentations of genus 0. In topology any deformation of a sphere is genus 0 and the segmentation is equivalent to an expansion of a balloon inside the intracranial volume resulting in one coherent volume.

Validation is carried out by comparing the automatic segmentation model to a semi-automated model. An example a segmentation of our proposed method is shown in Fig. 1(a) and example of the sample scheme with neighborhood connectivity is shown in Fig. 1(b).

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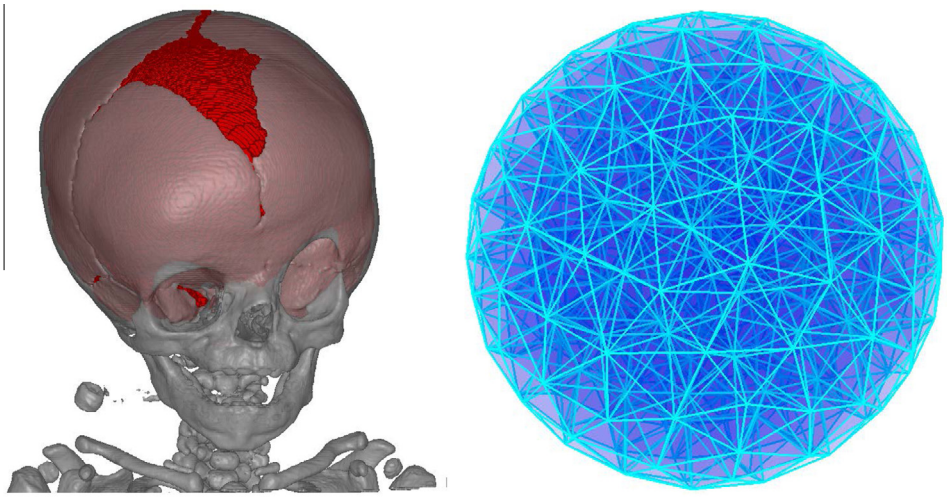

(a) ICV segmentation (b) Subsampling graph

Fig. 1. (a) shows the ICV segmentation shown in read of our proposed method overlayed with transparent bones in grey. (b) is an example of a spherical volume with equidistantly distributed nodes connected using Delaunay tetrahedralisation. The actual subsampling density is much denser than that shown in the image.

2. Brief review of the previous research

Current work on automatic ICV[1] estimation has focused on Magnetic Resonance Imaging (MRI) volumes [2–4]. However, these methods are not well suited for ICV estimation in craniosynostotic cases due to the limited bone-tissue contrast in MRI. In the case of craniosynostosis, the best contrast of the cranial bones, e.g. for diagnosis and surgery planning, is obtained from CT scans. Furthermore, standard methods often use atlases based on a normal population, which may lead to a bias in the estimation of the ICV in craniosynostotic cases. The current standard for ICV estimation from CT is a manual method based on thresholding followed by a seed-growing algorithm. The problem with this method is the need for manual editing in the various foramina in the skull base as well as in regions where craniosynostosis or lacking suture fusion have caused gaps between the cranial bones [5–7].

Anatomical segmentation such as the segmentation of the ICV in medical images is addressed in the literature by a series of approaches. In [8], deformable template matching is applied in a Bayesian setting; in [9], deformable surface models are proposed using a graph cut approach; and in [10], a multiclass Markov Random Field (MRF) is used for voxel classification. In the latter case it is interesting that, for two-class models, global optimal segmentation can be obtained using a graph-cut-based approach [11]. In this work we propose a two class segmentation of the ICV, where the classes (inside and outside) are modeled as mixtures of Gaussians. In addition to a label prior, we use a gradient-dependent interaction term. Moreover, we employ a tetrahedralisation of a spherical equidistant sample distribution leading to a graph. The graph has dedicated outside and inside nodes, which robustly forces the graph segmentation to be of genus 0.

3. Approach

The data consist of pre-surgical CT head scans of 15 children aged from 6 to 18 months and diagnosed with UCS (either left- or right-sided). Each child has an abnormal headshap/cranium due to due to the UCS and the data set does not constitute a normal distribution. The scans were obtained at 512 × 512 pixels in-plane resolution and a complete volume consists of between 167 and 350 slices. The scans were acquired at Copenhagen University Hospital except for one acquired at Helsinki University Central Hospital.

The aim of the method is to create a volumetric segmentation that follows the transition between brain matter and bone, while also closing holes in the bone structure. In order to learn statistics from the CT attenuation images, we fit a mixture of Gaussians to each individual scan. The mixture of Gaussians is carried out using expectation maximization and results in three normal distributions describing: skin, brain matter and bone (see Fig. 2). The variances of skin and bone are higher compared to brain tissue, which is used to classify the distributions unsupervised. Brain matter is by far the dominant, but also that with the least variance. Using the probability density function, where v is a sample value, we define the following two probabilities: $p(v|x = \text{ICV}) = \text{pdf}_{brain}$ and $p(v|x \neq \text{ICV}) = \text{pdf}_{skin} + \text{pdf}_{bone}$. Generally, the brain matter distribution fits well to the data, while the other two tissues just stay below and above both with a wider standard deviation. Using only the mixture of Gaussians to classify brain-tissue and non-brain tissue would lead to misclassification as the distributions are crude, while the proposed method is insensitive to this.

Before the segmentation, the volumes were interpolated in the slice-wise direction to create isotropic voxels and ensure a regular sampling. A graph is created on sampling points in the volumes. The sampling points are found using a spherical volume of

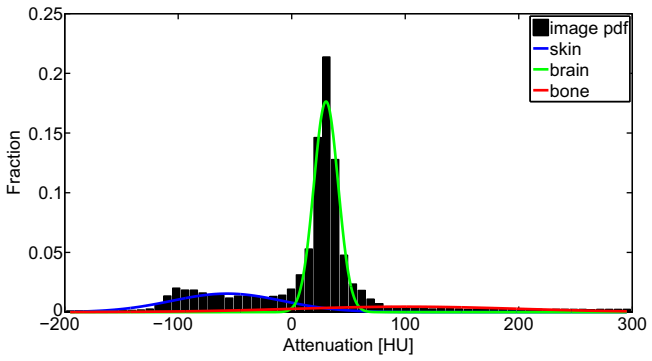

Fig. 2. A mixture of Gaussians shown on the intensity histogram of a CT scan. The higher and lower attenuation values have been clipped and are not shown in the graph.

[1] In MRI they often estimate the total intracranial volume (TIV).