021 **ACTIVE SHAPE MODELING TECHNIQUES IN OPHTHALMOLOGY: AUTOMATIC SEGMENTATION OF THE EYE IN MAGNETIC RESONANCE IMAGING OF CHILDEREN**

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Background: Delineation of ocular anatomy in 3D imaging involves a big challenge for ophthalmologists, mostly when developing the treatment planning for ocular diseases. Magnetic resonance imaging (MRI) is used today in clinical practice as a complementary source of information, together with fundus imaging or ultrasound, in diagnosis and treatment planning for retinoblastoma in children. Here we present a novel 3D statistical Active Shape Model (ASM)[1] to automatically segment the eye anatomy in the MRI.

Aims: To develop an Active Shape Model (ASM) based on 3D MRI for precise children eye segmentation.

Methods: Our data set is composed of 12 healthy eyes from children aged 3.2±1.7 years old. Imaging was performed a 3T Siemens TimTrio machine (Siemens, Erlangen, Germany), with a 32-channel surface head coil attached. The images are T_1-Weighted GE VIBE (TE/TR, 3.91/20 ms). The Dataset has images which were acquired at two different spatial resolutions of 0.416x0.416x0.399 mm and 0.48x0.48x0.5mm. All the volumes were resampled to a common space 0.416x0.416x0.399 mm for constructing the model.
The eye model comprises the regions of the lens, the vitreous humor, the sclera and the cornea. Manual delineations were done for all subjects and structures. They were corrected for all orthogonal planes by a senior radiation oncologist. The model construction is done by combining all the surfaces extracted from the manual delineation, generating a shape variation model, and coupling it with the intensity information to build the ASM as suggested in [2,3]. The segmentation of a subject works as follows. We first automatically detect the position of the center of the eye, the lens and the optic nerve, using the algorithm proposed in [4] for aligning the model. Afterwards, we proceed to do the fitting by minimizing the Mahalanobis distance between the ASM and the subject until convergence.
We quantitatively validate our segmentation method with a leave-one-out cross validation test. The resulting segmentation is assessed by the overlapping measure (Dice Similarity Coefficient, DSC) with the manual segmentation used as the ground truth (GT). Additionally, we provide a measure of the mean distance error of the given segmentation wrt. the GT for every region in the eye.

Results: Through the leave-one-out test for the ASM fitting, we obtain an average DSC of 96.68±1,24% for the sclera and the cornea, a 95.88±1,73% for the vitreous humor and 84.41±3,4% for the lens. The mean overall distance error is 0.20±0.09mm for both the sclera and the cornea and the vitreous humor. For the lens we reach an average error of 0.21±0.1mm. The entire segmentation process takes in total 8 s.

Conclusions: We have shown a reliable and accurate segmentation tool that enables clinicians to automatically delineate the sclera, the cornea, the vitreous humor and the lens in MRI. This tool will contribute to reduce the time spent in the tedious task of eye shape delineation and will eventually help clinicians during ocular tumor treatment planning and diagnosis confirmation.

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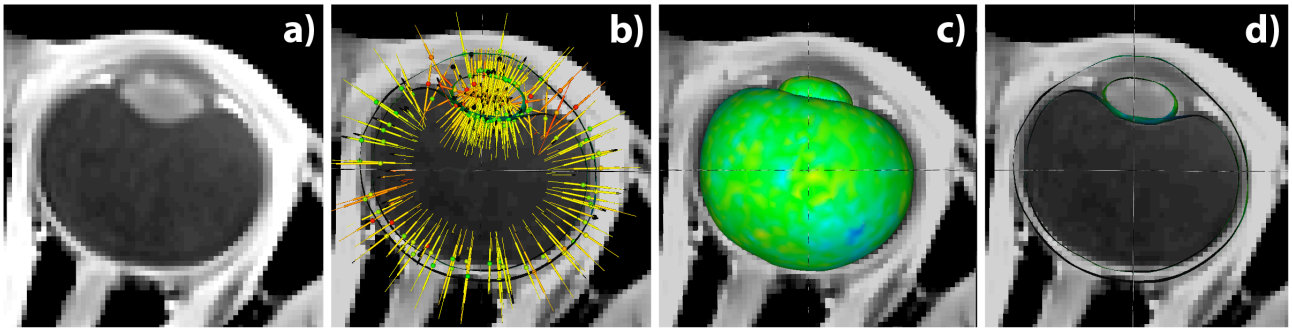

Figures: (a) Pre-processed MRI. b) Model Initialization c) Automatic Fitting. d) Final Segmentation.