Automatic segmentation of the fetal cerebellum using spherical harmonics and gray level profiles

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ABSTRACT

The cerebellum is an important structure to determine the gestational age, cerebellar diameter obtained by ultrasound volumes of the fetal brain has shown a high correlation with gestational age, therefore is useful to determine fetal growth restrictions. The manual annotation of 3D surfaces from the fetal brain is time consuming and needs to be done by a highly trained expert. To help with the annotation in the evaluation of cerebellar diameter, we developed a new automatic scheme for the segmentation of the 3D surface of the cerebellum in ultrasound volumes, using a spherical harmonics model and the optimization of an objective function based on gray level voxel profiles. The results on 10 ultrasound volumes of the fetal brain show an accuracy in the segmentation of the cerebellum (mean Dice coefficient of 0.7544). The method reported shows potential to effectively assist the experts in the assessment of fetal growth in ultrasound volumes. We consider the proposed cerebellum segmentation method a contribution for the SPHARM segmentations models, because it is capable to run without hardware restriction, (GPU), and gives adequate results in a reasonable amount of time.

Keywords: 3D Fetal Ultrasound Segmentation; Fetal Cerebellum, Statistical Shape Models; Spherical Harmonics.

1. INTRODUCTION

The Virtual Organ Computer Aided Analysis (VOCAL) techniques and cerebellar volumes obtained by multiplanar, have shown a high correlation with gestational age [1]. This techniques have shown differences between growth restricted fetuses and also adequacy for the assessment of the gestational age [2]. The growth of the cerebellum in normal pregnancy, using the multiplanar technique is evaluated [3,4]. Nevertheless this techniques have the disadvantage of the necessity of manual delineation by an experienced operator, an example of this can be seen in figure 1.

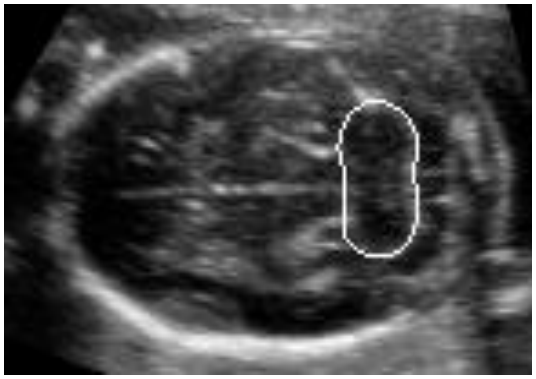

Figure 1 Manual segmentation of the cerebellum

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To ease the task for the experts and to contribute to improved reproducibility in the measurement of the cerebellar volume, we have explored the use of a spherical harmonic (SPHARM) model of the cerebellum for automatic segmentation of the structure in ultrasound volumes [5]. SPHARMs have methodological advantages for the construction of statistical models of 3D shapes: Only a small set of landmark points is required for registration of one object to another, therefore there is no need for extensive annotation of landmark points; Accurate shape modeling is achieved through principal components analysis of a set of normalized 3D shape examples. However, current methods for automatic adjustment of an SPHARM to a gray level image volume, require very intensive voxel processing [6]. In this work we report the development of a new strategy to automatically adjust an SPHARM to the cerebellum in a fetal ultrasound volume. Our strategy is based in the optimization of an objective function constructed from gray level profiles, sampled in the normal direction on each node of the mesh of the SPHARM. This results in a very efficient algorithm. In the rest of this work is reported the development of our SPHARM of the cerebellum and its use for the automatic segmentation of the structure in ultrasound volumes. In section 2 we report the construction of the SPHARM of the cerebellum trained from a set of 9 annotated ultrasound volumes. In section 3 we describe our new method used to automatically adjust the SPHARM model to an ultrasound volume based on gray profiles of the mesh vertices. In section 4 are reported the results from automatic adjustment of the SPHARM of the cerebellum to a set of 10 different non-training ultrasound volumes, using the leave-one-out method. In section 5 we present the discussion and conclusions of the work reported.

2. SPHARM MODEL OF THE CEREBELLUM

Our SPHARM model of the cerebellum was trained with 9 cerebellum shapes annotated by an expert on 15 slices of each ultrasound volume, as reported in Velasquez [5]. After annotation each cerebellum shape was discretized as shown in Fig. 2.

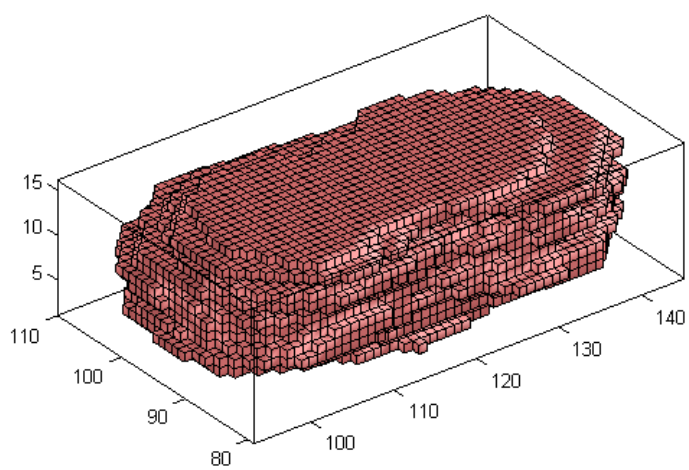

Figure 2 Discretized cerebellum example

The corresponding triangular mesh was generated for each shape using marching cubes [7].
Following the work of Shen [8] we constructed the SPHARM description of each of the points in the surface:

$$v(\theta,\varphi) = (x(\theta,\varphi), y(\theta,\varphi), z(\theta,\varphi))^T \quad (1)$$

The surface is then described by the vector valued function:

$$v(\theta,\varphi) = \sum_{l=0}^{Lmax} \sum_{m=-l}^{l} c_l^m Y_l^m(\theta,\varphi) \tag{2}$$

where the coefficients are 3D vectors corresponding to the 3 coordinate functions in (3):

$$c_l^m = (c_{lx}^m, c_{ly}^m, c_{lz}^m)^T \tag{3}$$

Using its decomposition in spherical harmonics we were able to model the 3D surface corresponding to each cerebellum volume in the training set. In Fig. 3 is illustrated an SPHARM model of one cerebellum, we can observe how shape details increase with the degree (L_{max}) of the SPHARM.

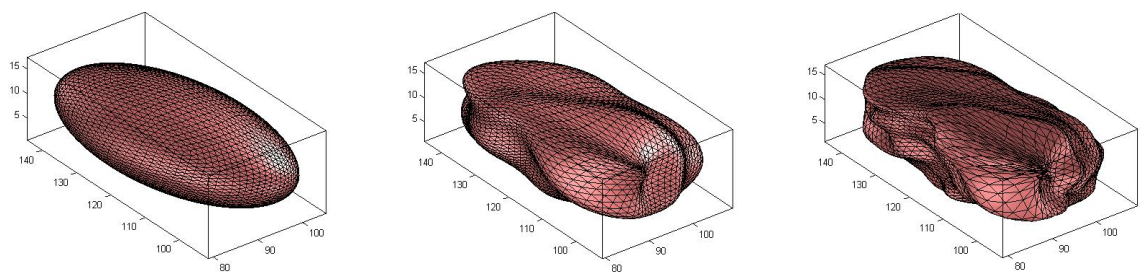

Figure 3. SPHARM of one cerebellum for an increasing degree (from left to right) L_{max} =1; L_{max} = 7; and L_{max} =15.

After we have a set of SPHARM coefficients for each of the 9 shapes in the cerebellum training set. A principal component analysis (PCA) of the shape parameters was performed through registration of all SPHARM models, using 6 corresponding landmark points on each shape [8].

As previously described in Velásquez [5] we used the Matlab toolbox SPHARM-MAT [8] to construct the SPHARM model of the cerebellum. This toolbox generates the parameterizations of each shape on a training set, performs the registration and calculates the mean shape and the main modes of variation (principal components of the covariance matrix). In Fig. 4 is shown our SPHARM model of the cerebellum for the main principal component.

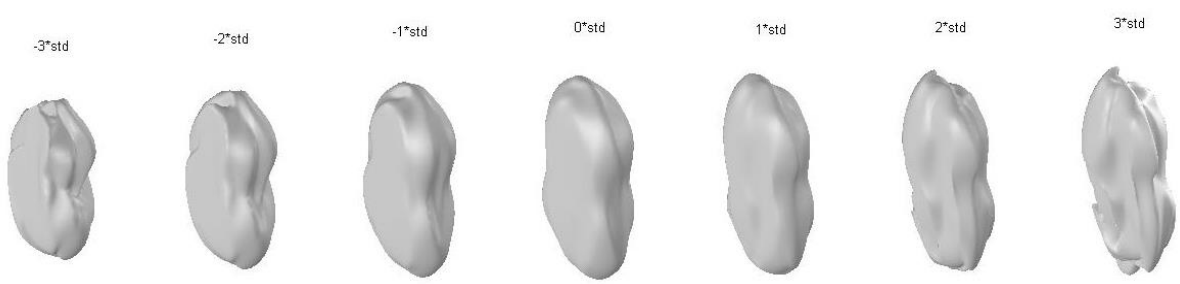

Figure 4 SPHARM based model of the cerebellum. Shape variation is shown for the main mode within the range ±3 standard deviations.

With this it is possible to generate to generate new shapes of the class of the training set (i.e. cerebellums) using Eq. 4.

$$S_\alpha = S_\mu + \sum_{i=1}^{M} \alpha_i S_i \tag{4}$$

Where:
S_μ is the mean shape
S_i, are the principal component vectors of the training set
α_i are the shape adjustment parameters

Our SPHARM model was used to automatically segment the surface of the cerebellum in fetal ultrasound volumes, as described in the following section.

3. SEGMENTATION BASED ON GRAY LEVEL VOXEL PROFILES

As suggested by Gutierrez [6], we can observe in the ultrasound images of the brain of the fetus that the cerebellum is a structure with a semi-defined edge. If we sample gray levels profiles which are normal to each vertex (Fig. 5) we can observe a pattern of bright gray levels at the center of the profile and darker gray levels at the extremes (as shown in Fig. 6). The profiles were obtained by sampling a voxel profile on each node of the mesh, in the normal direction to the surface of the SPHARM, as illustrated in figure 5.

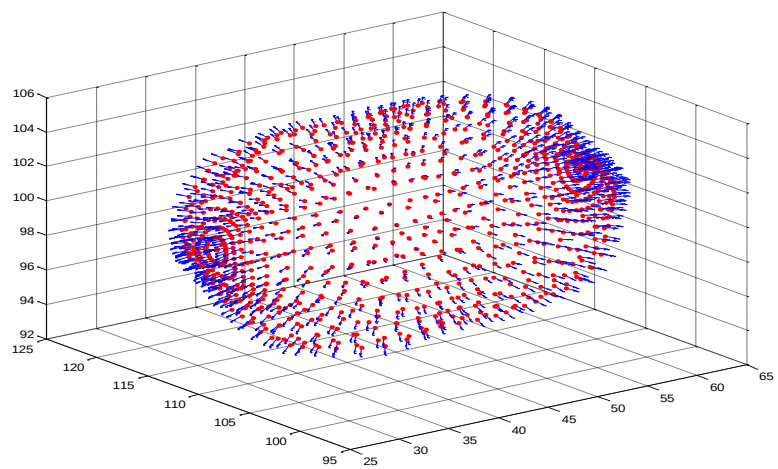

Figure 5 Normal to each mesh vertice.

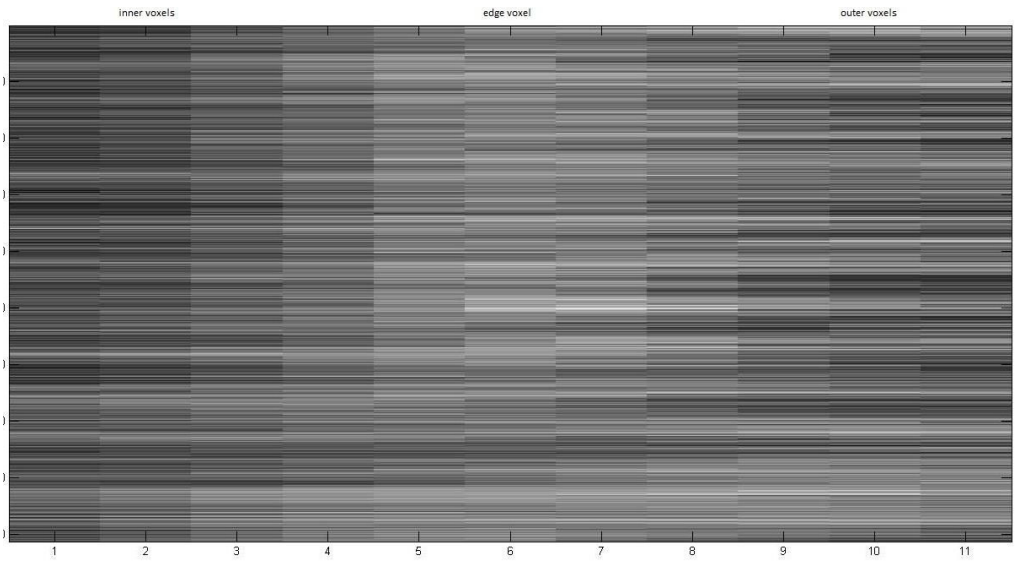

Figure 6 Cerebellum mesh vertices mean profiles of the
Obtained from the training set.

Each gray level profile has 11 voxels and was divided in three different groups, as described by Gutierrez[6]:

1. p_0 is the center of the profile, is supposed to be the brightest
2. The central positions p_{-1}, p_1, conformed by voxels that are near the edge, still bright, but not as the center voxel.
3. The first and last four positions of the gray profile are those voxels ($p_{-5}, p_{-4}, p_{-3}, p_{-2}\ and, p_2, p_3, p_4, p_5$) not as bright as the central positions.

The objective function was constructed to detect the border profile it was design to give minimum values when the SPHARM correspond to cerebellum surface in the ultrasound volume and its based on:

$$f_i = -2B - C + F \tag{5}$$

Where:

$B = p_0$

$C = p_1 + p_{-1}$

$$F = \sum_{j=-5}^{-2} p_j + \sum_{j=2}^{5} p_j$$

Considering p_j as the value of the gray profile in the jth position of the profile.

Finally the objective function F_{obj}value was calculated as the sum of the function f_i evaluated in each vertice of the mesh.

$$F_{obj} = \sum_{i=1}^{N} f_i \tag{6}$$

Where N is the number of vertices of the mesh of our statistic model, 1875.

In order to optimize this objective function, we used the Nelder–Mead [9] simplex algorithm. With this algorithm its possible to adjust the transformation of our model: scale (s), rotation over the z axis (θ_z) and translations (t_x, t_y, t_z) and the weights of the shape parameters (α_i) shown in equation 6. Adequate ranges were defined for each parameter: $(0.7-1.3)$ for scale, $(-\pi/4;\ \pi/4)$ for rotation, and $(-10, 10)$ voxels for the translation parameters.

4. TESTS AND RESULTS

We used 10 different ultrasound volumes acquired in an axial plane by a Voluson 730 Expert from General Electric, with a 4-8 MHz 3D probe. All volumes were acquired with informed consent of the patients at the National Institute of Perinatology in México City. Our cerebellum set was annotated by an expert sonographer.

The automatic segmentation of the cerebellum was evaluated on the training set using the leave-one-out method. 9 volumes were used for training the SPHARM of the cerebellum with validation of automatic segmentation on the volume left out. This was repeated 10 times, validating the automatic segmentation on each of the 10 fetal ultrasound volumes. The Dice Similarity Coefficient was used to measure the accuracy of the automatic SPHARM segmentation as compared against manual expert annotations.

We first use an anisotropic diffusion filter[10] to reduce the speckle, with 20 iterations and diffusion coefficient of 0.75. Later we initialize the mean SPHARM mesh model centroid inside the cerebellum area in each volume. The initial simplex was set using the mean shape from our SPHARM mesh model with no rotation or deformation (i.e. $\theta z = 0, \alpha_i = 0$). Since the cerebellum appeared in a similar initial position in all the images due to the acquisition methodology, the initial translation was set to be the mean translation of the training set. To stop the algorithm we considered a total of 100 iterations. The results are shown in table 1.

Table 1. Segmentation Results

Segmented volume	DSC
1	0.8264
2	0.7538
3	0.7430
4	0.6873
5	0.7718
6	0.7043
7	0.7259
8	0.7013
9	0.8353
10	0.7953
Mean	0.7544
Standard deviation	0.0521

In Figure 7 is shown the intersection between the volume annotated by the expert (red), and the corresponding automatic annotation (blue).

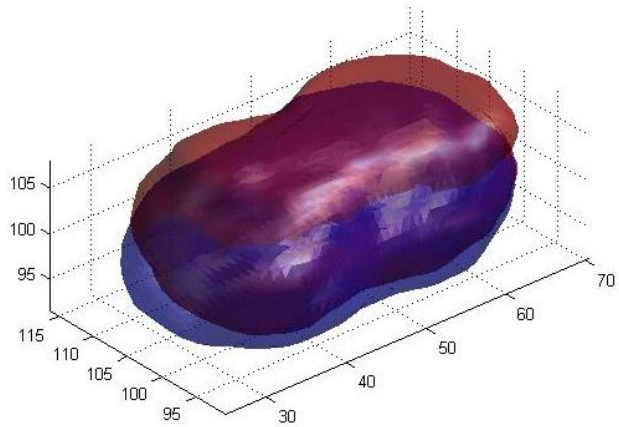

Figure 7 Comparison between automatic segmentation (blue) and manually (red)

5. DISCUSSION AND CONCLUSIONS

From table 1 can be observed that our method is able to automatically segment the cerebellum in an ultrasound volume with a mean DSC of 0.7544±0.0521. DSC values starting from 0.7 for ultrasound segmentations are considered a good agreement with the corresponding expert annotations. For future work we are considering to use different optimization methods such as gentetics algorithm or simulated annealing, also using some texture descriptor using the gray profiles.

An execution time around 1.5 minutes have been previously obtained by Ahmandi [11], but requires a computer with a GPU capable to run parallel algorithms, in other to determine the voxels inside and outside the mesh. This is necessary due the voxelization of the mesh is the principal holdup. Our gray profile algorithm do not require a GPU but takes a mean of 4.93 minutes (Matlab, i7 processor 4710 HQ with 8GB ram) to realize the segmentation. This time can be improved by using a minor degree for the SHPARM expansion, but it will be necessary to confirm that the DSC results do not change in a considerable way.

We consider that this proposed cerebellum segmentation method a contribution for the SPHARM segmentations models, because it is capable to run without hardware restriction, (GPU), gives adequate results in a reasonable amount of time, therefore can also be used in other brain or closed anatomical structures present in ultrasound volumes.

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