SEMI-AUTOMATIC SEGMENTATION OF PRETERM NEONATE VENTRICLE SYSTEM FROM 3D ULTRASOUND IMAGES

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ABSTRACT

3D Ultrasound (US) has been developed recently to image the intracranial ventricular system of pre-term neonates in order to monitor these patients for intraventricular hemorrhage (IVH) and the resultant dilatation of the ventricles. 3D US is capable of providing volumetric ventricle measurements, compared to clinically used 2D US, relying on linear measurements from a single slice, and visual and quantitative estimates to determine the severity of ventricular dilatation. In this work, we propose a convex optimization-based segmentation approach for 3D US images of the cerebral ventricles in preterm neonates with IVH. The proposed semi-automatic segmentation method makes use of the latest development in convex optimization techniques supervised by user interactive information. Experiments using 25 3D US images of 5 patients (5 time points for each subject) show that our proposed approach yielded a mean DSC of 78.9% compared to a manually contoured surface. This GPU-implemented semi-automated approach reduced the time required per segmentation by 1200% (mean times: 2.5 vs. 30 minutes). In addition, the intra-observer variability experiments showed that the variability introduced by the user initialization is small in terms of DSC, demonstrating a low intra-user variability.

Index Terms— 3D ultrasound imaging, ventricular segmentation, convex optimization, pre-term neonate, hydrocephalus, intraventricular hemorrhage

1. INTRODUCTION

Intraventricular hemorrhage (IVH), which is characterized by bleeding in and around the cerebral ventricles, is common among preterm infants with an occurrence of 12-20% in those born at less than 35 weeks gestational age with a low birth weight (< 1500g) [1]. The diagnosis of IVH is done using 2D clinical ultrasound (US). Patients often have a period of ventriculomegaly (ventricle dilatation) that spontaneously resolves, but some fraction of those will progress to hydrocephalus, an abnormal, progressive accumulation of cerebral spinal fluid (CSF), which requires an intervention to cease the accumulation of CSF inside the ventricles and prevent further brain injury. 3D US can be used to monitor the neonatal ventricular system [2] at the bedside. However, to attain the clinically relevant ventricle volume, the ventricles must be segmented in the image. Although manual segmentation can be used, it is arduous and time consuming (30-45 minutes for one 3D image), and requires much expertise, making this approach clinically not feasible. Therefore, an automated or semi-automated segmentation algorithm would be highly desired to adequately reduce the time and workload required to obtain the ventricle volume from the 3D US image in lieu of manual segmentation.

Previous cerebral ventricle segmentation algorithms have been exclusively developed for CT [3] or MR images [4], and used primarily in adult populations. While studies have quantified 3D US ventricle volumes in neonates [2], all have used manually contoured regions. Unlike in a healthy neonate, IVH patients ventricles provide unique challenges to segment, due to irregular shape deformation as well as poor image quality, such as missing edges, inhomogeneity, US speckle, artifacts caused by patient movements, hyperechogenicity from blood clots or the highly vascularised choroid plexus, as shown in Fig. 1. These challenges make most threshold or local optimization based methods, such as the classic active contour [5] and level set [6], not useful for this application. Atlas based segmentations fail as dilation and subsequent reduction of surrounding cerebral matter cause deformations to the structure that cannot be easily accounted for and vary drastically from patient to patient. Thus, accurate and efficient automatic or semi-automatic ventricle segmentation is highly desired in order to translate 3D US into clinical practice. In [7], we reported the first study on semi-automatic segmentation of lateral ventricles in neonates with IVH from 3D US images, which yielded a mean dice similarity coefficient (DSC) of 72.4%. However, it requires pre-segmented
ventricles at baseline as shape priors and six user selected landmarks for initialization. The complicated procedures make it difficult to be applied in a clinical setting.

In this study, we propose a convex optimization based approach for semi-automatic extraction of lateral ventricles of premature neonates from 3D US images. This method makes use of the local appearance model of ventricles combined with user initialization. The introduced segmentation problem can be solved by convex relaxation supervised by the information from user initialization, and implemented on GPU to achieve a speed-up in computation.

2. METHOD

2.1. Initialization

The proposed segmentation approach first requires users to label some voxels inside and outside ventricles as foreground and background on a few sagittal views, using a 3D paint brush in ITK-SNAP [8], as shown in Fig. 2. The intensities of the labeled voxels are used to estimate two prior intensity probability density functions (PDFs) for the foreground and background, respectively, which serve as a data cost to facilitate the subsequent optimization procedure. The user stroked voxels also act as hard constrains supervising the optimization procedure.

2.2. Supervised Convex Optimization Based Segmentation

In this work, a convex optimization based method is used to obtain the optimal segmentation, while implicitly encoding the prior information of user labeled foreground \( \Omega_f \) and background \( \Omega_b \) voxels in the initialization procedure.

We propose to partition the given 3D image \( I(x), x \in \mathcal{R} \), into two parts: foreground (\( \mathcal{R}_f \)) and background (\( \mathcal{R}_b \)), by achieving the minimum total labeling cost combined with the minimum total area of all the segmented regions, such that

\[
\min_{u(x) \in \{0, 1\}} \left\{ \langle u, D(x) \rangle + \int_{\mathcal{R}} g(x) |\nabla u(x)| \, dx \right\}
\]  

where the first term is used to label each voxel to be in the ventricle region or the background region by the log-likelihood of the respective intensity PDFs (\( I \)), according to [9]; the second term \( dist(\Omega_f) \) measures the Euclidean distance between each voxel with the user stroked foreground region.

Let \( u(x) \in \{0, 1\} \) be the indicator or labeling function of the region \( \mathcal{R}_f \), such that

\[
u(x) := \begin{cases} 
1, & \text{where } x \text{ is inside } \mathcal{R}_f \\
0, & \text{otherwise}
\end{cases}
\]

Therefore, the optimization problem (1) can be reformulated in terms of the defined labeling functions \( u(x) \in \{0, 1\} \) as follows

\[
\min_{u(x) \in \{0, 1\}} \left\{ \langle u, D(x) \rangle + \int_{\mathcal{R}} g(x) |\nabla u(x)| \, dx \right\}
\]

where \( g_i(x) \geq 0 \) gives the non-negative edge weight function and each weighted total-variation function of (3) measures the weighted area of the surface \( \partial \mathcal{R} \), given by

\[
g(x) = \lambda_1 + \lambda_2 \exp(-\lambda_3 |\nabla I(x)|), \quad \lambda_{1,2,3} \geq 0.
\]

2.3. Convex relaxation and continuous max-flow algorithm:

To optimize the energy function (3), which is often highly nonlinear, we introduce the convex optimization based approach [10], which can efficiently move the given surface to the object of interest at its globally optimal position by globally solving the following continuous min-cut problem:

\[
\min_{u(x) \in [0, 1]} \left\{ \langle 1 - u, C_s \rangle + \langle u, C_I \rangle + \int_{\mathcal{R}} g(x) |\nabla u| \, dx \right\}
\]
where the functions $C_{s,t}(x)$ for the respective foreground and background are set up w.r.t. the current surface according to (2). The continuous min-cut problem (5) can be solved globally and efficiently by means of the continuous max-flow method [10]. To incorporate the user stroked voxels in region $\Omega_f$ and $\Omega_b$ as hard constrains into the continuous max-flow algorithm, $C_s(\Omega_f)$ and $C_t(\Omega_b)$ are assigned to zeros. The supervised continuous max-flow algorithm is implemented on the modern parallel computing platforms (GPUs) to obtain the high-performance in computation. For more details refer to [10].

3. EXPERIMENTS

Image acquisition: A motorized 3D US system developed for cranial US scanning of pre-term neonates using a 2D US transducer (Phillips C8-5 broadband curved array) was used for image acquisition [11]. To perform a scan, an US technician locates the third ventricle, which is midline through the anterior fontanelle, and then the 3D US system mechanically tilts the 2D transducer to acquire a full image of the ventricular system. Imaging was performed with a 60-72 degree scan angle, a step size of 0.3 degrees at a frame rate of 25 frames/s with total scan times between 8.0-9.6 seconds. The image sizes ranged from $300 \times 300 \times 300$ to $450 \times 450 \times 450$ voxels at the same voxel spacing of $0.22 \times 0.22 \times 0.22 \text{mm}^3$. The scans were performed 1-2 times per week for the first month enrolled in the study and 1-4 per month for the duration of the patients’ stay in the neonatal intensive care unit. In this study, twenty five 3D US images of five patients (five time points for each patient) were used to validate the proposed segmentation approach.

Evaluation metrics: A manual segmentation of each image used as the ground truth was compared to the algorithm segmented result, using volume-based metrics: Dice similarity coefficient (DSC); distance-based metrics: the mean absolute surface distance (MAD) and maximum absolute surface distance (MAXD); and volume measurement metrics: volume difference (VD), $|V_{\text{Manual}} - V_{\text{algorithm}}|$. In addition, each image was segmented three times by the same observer for assessing the intra-observer variability.

Implementation details: The initialization was performed in ITK-SNAP software [8]. The GPU based algorithm was developed with non-optimized Matlab (Natick, MA) code based on single-thread programming, which were run serially on a Windows desktop with an 4-core Intel i7-2600 CPU (3.4 GHz) and a NVIDIA Geforce 5800X GPU. The segmentation time was calculated as the mean run time of three repeated segmentations for each 3D US image to assess the algorithm’s efficiency.

4. RESULTS

Accuracy: Figure 3 shows one example of the algorithm segmented lateral ventricles of one patient. Visual inspection shows that the algorithm segmented surface (green contours) agree well with the manual delineations (red contours). Quantitative segmentation results in Table 1 shows that the proposed approach yielded a mean DSC of $78.9 \pm 3.4\%$, a MAD of $0.7 \pm 0.2 \text{mm}$, a MAXD of $5.3 \pm 4.2 \text{mm}$, and a VD of $2.5 \pm 2.9 \text{cm}^3$ for the 25 patient 3D US images.

Variability: The result of the intra-observer variability test showed that the proposed method yielded a DSC of $76.8 \pm 3.1\%$, $78.9 \pm 3.4\%$ and $80.0 \pm 3.7\%$ for three segmentations from the same observer, respectively. ANOVA analysis with a single factor failed to demonstrate a statistically significant difference between these three segmentations ($p = 0.55$, $F = 0.60$), suggesting a high reproducibility.

Computational time: The mean run time of the convex optimization algorithm was $15 \pm 2 \text{ s}$ in addition to $120 \pm 5 \text{ s}$ for initialization, resulting in a total segmentation time of less than $2.5 \text{ minutes}$ for a 3D lateral ventricle US image, significantly less than 30 minutes required by manual segmentation.

5. DISCUSSION AND CONCLUSION

This paper proposes an accurate and efficient approach to the challenging segmentation problem of 3D US of the ventricular system in preterm infants with IVH. The proposed semi-automatic segmentation method makes use of the latest development of convex optimization technique supervised by user interactive information. The experimental results show that our proposed method is accurate with a mean DSC of $78.9\%$ for 25 3D US images of 5 patients (5 time points for each subject), which is higher than $72.4\%$ obtained in our previous study [7]. In addition, the intra-observer variability experiment showed that the variability introduced by the user initialization is small in terms of DSC, which demonstrates that the proposed method has a low intra-observer variability.

Although the current algorithm is semi-automatic, the 2.5 min computational time is reasonable to implement in a clinical setting, compared to 30-45 minutes required by a currently used manual segmentation. Another significant advantage of the proposed method is that it requires much less expertise and workload compared to manual segmentation. The algorithm performance suggests that it can be potentially used for measuring the volume of lateral ventricles of pre-term infants.
neonates. However, the single-observer manual segmentation used as ground truth in this study may be inaccurate. Notably, the manual segmentation for this particularly tough problem might achieve high inter- and intra-observer variability, especially for the regions of posterior and inferior horn of ventricles where uncertain boundaries often occur, as shown in Fig. 4 showing the segmentation result with the lowest DSC. The investigation on inter- and intra-observer variability as well as other volume measurement metrics will increase the credit of this study, which is one of our future works. In addition, although many methods have been developed to segment brain anatomical structures in 3D MR images, they are application dependent, and as such cannot be directly applied to 3D US images. Incorporating more information, such as texture and shape priors, into the current segmentation framework would improve the accuracy and efficiency.

6. REFERENCES


