Estimating Skull Thickness of Neonates Using Magnetic Resonance Imaging

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Abstract: Successful imaging of electrical activity in newborn infants is highly dependent on accurate and/or adequate representation of head representation from structural point of view. Namely, the electrical activity and the corresponding electroencephalography (EEG) measurements are dependant on electrical properties of brain and skull tissue i.e. corresponding conductivities and geometry of the skull and brain. Automated procedure for geometry/structural analysis are sparse even for adults and almost non-existent for neonates and newborn infants. In this paper we propose to develop automatic procedures for analyzing skull geometry and potentially other shapes/sizes that are relevant for electrical imaging of the cortex activity. To this purpose we propose to estimate the thickness of the skull using magnetic resonance (MR) images as a preliminary step in obtaining/estimating relevant structural parameters. Since the number of MR images is rather limited due to the age of the patients we develop a semi-supervised machine learning algorithm in which certain number of MR slices is used for training. We demonstrate applicability of our preliminary results using real MR images obtained from the University Children's Hospital, University of Belgrade, Serbia.

1 INTRODUCTION

Neonatal convulsions are one of the most common emergency neurological events in the early period after birth with the frequency of 1.5 to 3 in 1000 live births (Volpe, 2001). Consequently, neonatal intensive care units (NICU) continuously monitor electrical activity of preterm infants for both short-term and long-term interventions and/or treatments (Shellhaas and Clancy, 2007) The corresponding analysis of the electrical activity is usually based on so called inverse techniques and models that perform imaging of the cortical electrical activity (Asadzadeh et al., 2020). Most of the existing solutions utilize combination of EEG (excellent temporal resolution and poor spatial resolution) as a source of electrical activity information and magnetic resonance imaging (MRI, excellent spatial resolution and poor temporal resolution) as a source of geometry information and combine them in so called inverse models that are then used in order to estimate the unknown parameters (usually some type of constrained spatial source models such as distributed dipoles). In infants, however, accurately describing the anatomy of the head remains a challenge due to the complexity of the infant skull from the electromagnetic point of view. The importance of adequate representation of the skull in computational models has been recently demonstrated in (Antonakakis et al., 2020).

To this purpose in this paper we propose to estimate the thickness of the skull, as one of relevant parameters, using MR images and machine learning edge detection algorithms. We combine multiple edge detection algorithms using blind information fusion techniques that represents extension of our previous results (Liu et al., 2011). Although computed tomography (CT) is a much better candidate for automatic analysis of the skull thickness (Benson et al., 2022), (Lillie et al., 2016) due to the fact that in MR images skull tissue appears with pixels with lower intensity (dark regions) the radiation levels are often not acceptable in neonates and newborn infants. Although MR imaging is a feasible alternative even that technique is rarely done resulting in relatively small number of available images. Due to the limited size of the available data points for training we utilize the hybrid approach: a) we select certain number of volumetric slices for training and calculate the information

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fusion weights based on the anomalies we calculate from the training data set, b) we validate the proposed algorithms using the training data set and c) we evaluate the performance of the proposed algorithm on the remaining volumetric slices not previously used. Although the data points correspond to the same patients (i.e. similar geometry of the skull) our aim in this paper is only to show the proof of concept and further investigation of the performance is left for future work. The proposed algorithm consists of several stages: a) using superpixels (Achanta et al., 2002) algorithm we extract regions that are potential candidates for boundary region, b) within the boundary region we utilize several edge detection algorithms and evaluate anomalies (probabilities of errors) for two classes problem (inner and outer boundary) by utilizing semi-automatic selection of boundaries (manually labeled using edge detection algorithms), and c) we run the proposed algorithm using the anomalies from b) and performing information fusion on the volumetric slices not used for training.

In Section 2 we present mathematical and signal processing models as well as stages describing the proposed algorithm. In Section 3 we illustrate numerical results using a real data set obtained from the neonatal volumetric data of a neonatal subject. In Section 4 we discuss conclusions and outline directions for future work.

2 SIGNAL PROCESSING

We use realistic geometry of the 9 months old infant obtained at The University Children Hospital, University of Belgrade, Serbia. MRI images consisted of 110 axial MR slices with 256x256 size and field of view of 240 mm. The sample of volumetric slice produced in Slicer using DiCom folder is illustrated in Figure 1. The algorithm operates in the following way:

- Select volumetric slice for training, example illustrated in Figure 2
- Apply superpixel algorithms, output examples illustrated in Figures 3 and 4
- Apply three different edge detection algorithms: Sobel, Canny, Pickwitt, and log sample output of the algorithms illustrated in Figure 5
- Perform fusion using the local decisions and weighting coefficients calculated so that the probability of misclassification of the training set is minimized
- Perform outer boundary classification followed by inner boundary classification

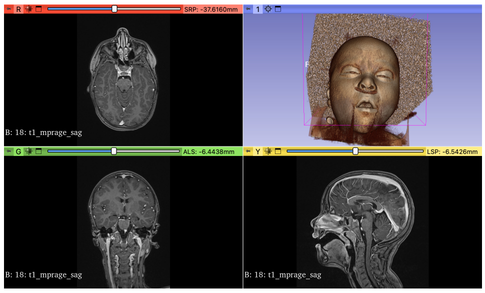

Figure 1: MRI of Infant Head.

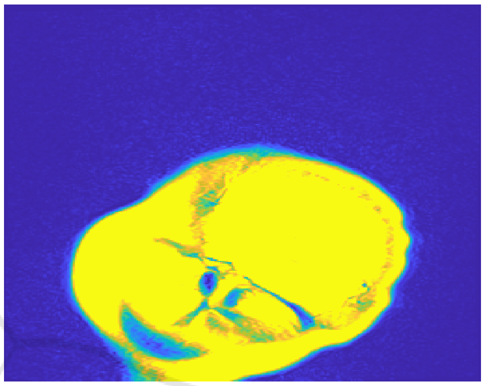

Figure 2: Sample volumetric slice.

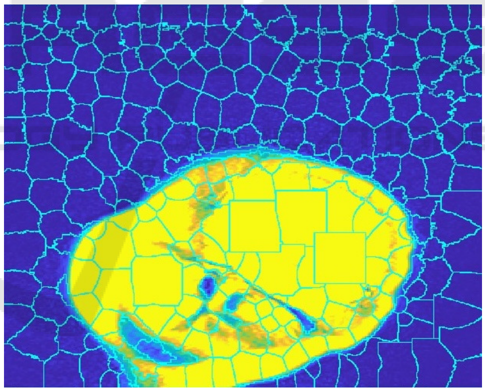

Figure 3: Initial Superpixel boundaries of the training slice.

In Figure 6. we illustrate the schematic of the proposed algorithm. The first step is identification/classification of the outer boundary points consisting of two hypothesis/classes

- H_0 not an outer boundary point
- H_1 outer boundary point

The global decision is then made by extending our previously reported results on optimally distributed detection of multiple hypothesis (Liu et al., 2011). Using a centre of pixel mass after the thresholding the distance for each of the edge points is calculated and for angle $\Delta\Theta = 1/256$ (min angular resolution of 256x256 image) we calculate maximum distance of

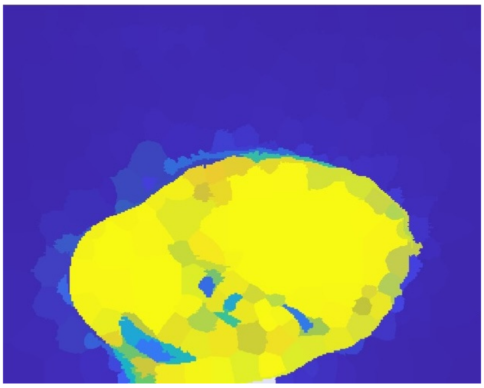

Figure 4: Superpixel clustering of the training slice.

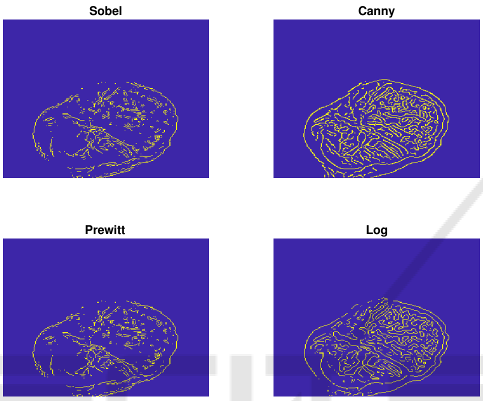

Figure 5: MRI of Infant Head.

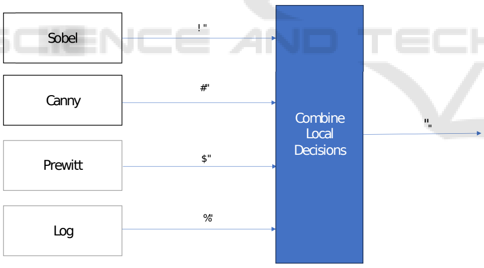

Figure 6: Information Fusion Scheme.

the non zero points. Note that edge algorithms produce pixels with intensity 0 and 1 and thus for a given angle we find the pixel along the radial line that has the largest possible distance thus producing $Rmax(\Theta)$. Therefore the j-th detector decision function is given by

$$u_{ij} = \begin{cases} 1 & \sqrt{(C_x - x(i))^2 + (C_y - y(i))^2} \\ 0 & \text{elsewhere} \end{cases}$$

The global decision is made in the following way: let u_{ij} be local decision for each of the edge detector algorithms, the global decision is made as

$$\hat{u}_j = \begin{cases} 1 & \sum_{i=1}^{4} w_{ij} * u_{ij} > 0 \\ 0 & \text{elsewhere} \end{cases}$$

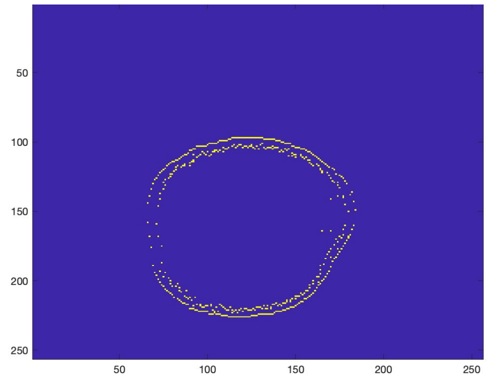

Figure 7: Outer and inner boundaries for a sample slice.

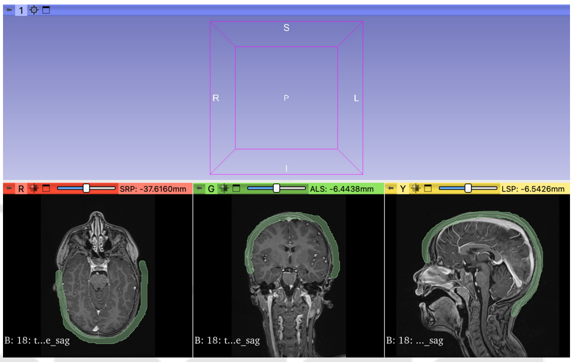

Figure 8: Skull thickness segment.

The weight coefficients are calculated using parametric model of Gaussian distribution mixture based on the distance between point $(x(j), y(j)$ and centre of the volumetric slice and calculating them so that the overall probability of error for both boundaries is minimized. Once the outer boundary is identified, the outer boundary points $\mathcal{S}_1$ points are removed and the algorithm is repeated in a same way so that the new set of outer boundary points is obtained and these points are then labeled as inner boundary points $\mathcal{S}_2$. The distance between the two sets is calculated using sliding window polynomial approximation (splines) and calculating perpendicular distances to estimate the thickness of the skull at that point.

3 NUMERICAL RESULTS

To illustrate the applicability of the proposed technique we perform preliminary performance evaluation on an MRI scan of the neonatal patient admitted to Children's Hospital, University of Belgrade, Serbia. The scan was obtained using 1.5 Tesla Siemens MR scanner resulting in 94 volumetric slices with resolutions (256x256 to 406x448). In this study we utilize 30 volumetric slices obtained using MRI rage

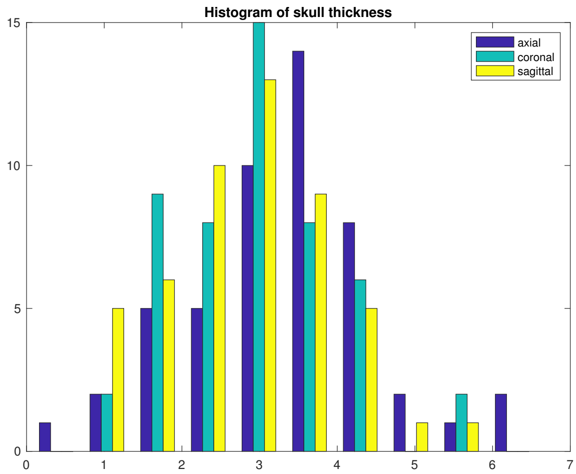

Figure 9: Histogram of skull thickness.

sequence in sagittal plane. For illustration purposes the output for one slice is illustrated in Figure 7 with clearly indicated outer and inner boundaries. The resulting mask for all the slices is illustrated in Figure 8 using Gaussian distribution as a thickness model and illustrating the region corresponding to three standard deviations for the actual slices. This mask was obtained using shift one approach in which 29 slices are used for training and 1 slice for evaluation. In this way we were able to determine boundaries in all the slices using the remaining 29 slices for training. In this way, our evaluation is performed blindly i.e. the evaluation part of the data set is never used for the training.

4 CONCLUSIONS

We proposed computational framework for calculating the skull thickness in the neonates using MR imaging that can potentially be used for improving the performance of the source imaging/localization algorithms for estimating electrical activity of the neonatal brain. Understanding electrical activity of the brain in infants is rather important as it can potentially predate the onset of certain pathological conditions. Since the relationship between the cortical activity and EEG signal measured on the skull depends significantly on the thickness of the skull we believe that the aforementioned techniques can improve such performance. We were able to demonstrate the ability to calculate the thickness of the skull and the actual validation of the results and comparison to geometry measurements obtained using in-vitro studies as well as Brain Suite tool (Shattuck DW, 2002) is left for future work.

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