

1 A Survey On Image Segmentation Using Decision Fusion Method

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6 Abstract

7 Neonatal brain MRI segmentation is challenging due to the poor image quality.Existing
8 population atlases used for guiding segmentation are usually constructed by averaging all
9 images in a population with no preference. However, such approaches diminish the important
10 local inter-subject structural variability. Tissue segmentation of neonatal brain MR images
11 remains challenging because of the insufficient image quality due to the properties of
12 developing tissues. Among various brain tissue segmentation algorithms, atlas-based brain
13 image segmentation can potentially achieve good segmentation results on neonatal brain
14 images. Atlas-based segmentation approaches have been widely used for guiding brain tissue
15 segmentation. Existing brain atlases are usually constructed by equally averaging
16 presegmented images in a population. However, such approaches diminish local inter-subject
17 structural variability and thus lead to lower segmentation guidance capability. To deal with
18 this problem, we propose a multi-region-multi-reference framework for atlas-based neonatal
19 brain segmentation.

20

21 *Index terms*— MRI segmentation, brain tissue segmentation,

22 1 INTRODUCTION n Neonatal Brain MRI Segmentation By 23 Building Multi -Region-Multi -Reference

24 Atlases, Brain tissue segmentation, which classifies brain tissues into meaningful structure such as gray matter
25 (GM), white matter (WM), and then cerebrospinal fluid (CSF).The segmentation is performed in this structure
26 is difficult in neonatal brain image due to low spatial resolution ,insufficient tissue contrast ,and ambiguous tissue
27 intensity distribution.

28 Due to these problem difficulties image intensity is insufficient for effective neonatal brain MRI segmentation.
29 The knowledge-based algorithm is seems to be effective. The atlas is build with multiple individual atlases with
30 decision fusion strategies. The strategy implies that individual atlas-based segmentation fuse the segmentation
31 into final result. Prastawa constructed an atlas by averaging 3 semiautomatic segmented neonatal image are
32 alignment using affined transformation. Weisenfeld obtained an unbiased atlas by averaging the probability
33 maps of 20 newborn subjects. Which are non-rigidly aligned with a simultaneous group-wise registration .a
34 multi-region -About ? -M.phil Scholar, P.S.G.R. Krishnammal College for Women, Coimbatore. Email id:
35 janumphil@gmail.com About ? -Assistant Professor BSc Dept., P.S.G.R. Krishnammal College for Women,
36 Coimbatore. multi-reference approach, which estimates multiple atlases for different anatomical regions. Subject
37 specific atlas is constructed for more effective neonatal segmentation.

38 There are two issues, taking brain as a single entity assign weight globally to all vowels so that a local shape
39 patterns in the brain will be desired. The parcellation is performed to separate the brain into multiple sub
40 regions. So that atlas can be build for each region separately. A cluster technique called affinity propagation is
41 used to cluster the images.

42 In In atlas based image segmentation algorithms, the segmentation performance is affected by the registration
43 procedure. The image acquired at late time brain image such as two-years old can achieve high accuracy using

44 the existing segmentation method like fuzzy clustering. The proposed method is to use latetime point image in
45 conjunction with its segmentation result as subject-specific tissue probabilistic atlas to guide tissue segmentation
46 of neonatal image. The subject-specific atlas can be used within a jointregistration-segmentation.

47 In Construction of Multi-Region-Multi-Reference Atlases For Neonatal Brain MRI Segmentation, Atlas can
48 be grouped into two categories1) average -shape atlas method ??prastawa et.,2005;song et al.,2007;xue et.,
49 2007)2)multi-classifier decision fusion methods, multi subjects in a population are selected as individual atlases
50 to independently guide segmentation.

51 Single atlas may not sufficiently characterize shape variation in a population; the atlas-based segmentation
52 approach has the drawbacks. The brain is taken as a single entity, different brain images regions have different
53 anatomical pattern as region-wise comparison approach may be more appropriate. A single average shape atlas is
54 generating from a population, it is better to construct multiple atlases. To I overcome these 2 issues a method for
55 each query image a subject specification is accommodated to the structural shapes of the query image. First the
56 averageshape atlas of a population images is divided into multiple regions. Each sub-population is represented
57 an exemplar and each its regions is represented by multiple exemplars. Collection of regional exemplar is called
58 multi-region-multi-reference atlas. A query image, one best match exemplars is selected for each region and
59 the selected exemplars for all regions are combined to form the final subject-specific atlas. A jointregistration-
60 segmentation strategy is finally used to segment the query image. Experiment result indicates that, in significant
61 segmentation accuracy improvement can be achieved.

62 2 II.

63 3 DECISION FUSION METHOD

64 Detecting edges in each image separately and then fusing the results is called decision fusion method.

65 4 a) Process of Decision Fusion

66 In neonatal brain MRI segmentation by building multi -region-multi -reference atlases, To build the atlas as prior
67 knowledge and to aid segmentation three strategies are commonly used 1) single individual atlas 2) average-shape
68 atlas 3) multiple individual atlases with decision fusion. The category 3 implies that the individual-atlas-based
69 segmentation multiple times with different atlas subject and then fuse the multiple image segmentation into a
70 final result with majority voting rule. It is to be noted that computation cost is quite high due to multiple
71 segmentation.

72 In neonatal brain image segmentation in longitudinal MRI studies, The decision fusion is widely used
73 to combine multiple segmentation into final decision with compensation for errors in single segmentation
74 ??Heckerman et al., 2006;Warfield et al., 2004). Decision fusion technique could be used to achieve better
75 neonatal segmentation. The concept of decision fusion is used to fuse the multiple image segmentation into a
76 single segmentation, with the single segmentation the neonatal brain MRI can be segmented easily. The need of
77 decision fusion is to fuse multiple image segmentation and to get the final result.

78 In Construction of multi-region-multi-reference atlases for neonatal brain MRI segmentation, Atlas construc-
79 tion methods can be roughly grouped into two categories1) average-shape atlas methods 2) multiclassifiers decision
80 fusion methods. In multi-classifier decision fusion methods, multiple subjects in a population are selected as
81 individual atlases to independently guide segmentation. All segmentation results from different atlases can then
82 fused by a majority-voting rule.

83 5 III.

84 6 METHODOLOGY

85 In Neonatal Brain MRI Segmentation By Building Multi -Region-Multi -Reference Atlases, The multi-region-
86 multi-reference framework for neonatal segmentation is carried out using neonatal images of 10 neonatal subjects
87 (6 males & 4females) with age ranging from 26 to 60 days. For evaluation process 2 sagittal, 3covonal, &3
88 transverse slices of images are manually segmented by expert. The proposed method was compared with manual
89 segmentation .The Dice ratio (DR) is used to measure tissue overlap rate for manual segmentation and automatic
90 segmentation. The approach was evaluated with 2 other atlases. The first method (population A) was created
91 76 infants with ages ranging from 9 to 15 months. The second method (population B) uses the population atlas.
92 To compare population A&B the joint registration -segmentation strategy is used to segment the brain images.
93 It is to be said proposed method yield a good result. Decision fusion is used with multiple atlas because single
94 atlas does not give a good result. Multiple atlases are carried out independently.

95 A multi-region-multi-reference framework for neonatal brain image segmentation is proposed in this paper.
96 For representing the local shape variation, multiple atlases are selected. Experimental results demonstrate that
97 our method yield the highest agreement with manual segmentation and brings out two population-atlas based
98 segmentation methods.

99 In Neonatal Brain Image Segmentation in Longitudinal MRI Studies, MRI images of neonates were performed
100 with more than 180 subjects. MRI scanning was performed using a 3T siemens scanner .In 10 subjects (4

101 females and 6 males) their neonatal images have been manually segmented. manual image segmentation was
102 mainly focused on 2 sagittal slices, 3 coronal slices and 3 axial slices. Segmentation was based on intensity based
103 clustering method and then manually edited with ITK-SNAP software (Yushkevich et al., 2006). In 10 subjects
104 with both one-year-old and two-year-old images. We use both of them to guide neonatal image segmentation
105 separately. To measure the overlap rate between two segmentation we use dice ratio (DR). The decision fusion
106 technique could be potentially used to achieve better neonatal segmentation performance, by combining the
107 segmentation results from multiple subject-specific atlases.

108 A framework is presented by using subject-specific tissue probabilistic atlas. The experimental results
109 demonstrate that subject-specific atlas has superior performance compared to the population-based atlases, and
110 the proposed algorithm achieves comparable performance manual raters in neonatal brain image segmentation.
111 The average total computation time is around 28 min for segmentation of a $256 \times 256 \times 198$ image with $1 \times 1 \times 1$
112 spatial resolution on a pc with 2.5 GHz Pentium 4 processor. 3 min is used for segmentation of a late time point
113 image for generating a subject-specific atlas, 14 min is used for atlas-to subject registration, and 11 min are used
114 for atlas-based neonatal image segmentation. It is to be concluded that proposed segmentation framework is able
115 to achieve satisfactory segmentation results with reasonable computational time.

116 In Construction Of Multi-Region-Multi-Reference Atlases For Neonatal Brain MRI Segmentation, The
117 proposed multi-region-multi-reference neonatal segmentation framework was applied to 10 subjects. 10 image
118 were manually segmented by expert rater using ITK-SNAP (Yushkevich et al., 2006). Central brain region was
119 not segmented due to extremely low tissue contrast. The proposed segmentation algorithm was compared with
120 that of manual segmentation. The tissue overlap rate is compared with dice ratio (DR). The decision fusion is
121 used to fuse the multiple image segmentation into single segmentation and the fused images are used for
122 manual segmentation and the result yields a good result. Our method yields the highest agreement with manual
123 segmentation and outperforms the two average-shape atlas-based segmentation method. If the given population
124 includes subject with a broad range of ages, the constructed multiple atlases in each region will learn all the
125 shapes from different ages. It is to be concluded that multi-region-multi-reference atlas makes it adaptable to a
126 large range of datasets. The methods such as brain parcellation, similarity measurement and image clustering
127 can be further refined and optimized.

128 From this survey on image segmentation using decision fusion gives good result on neonatal images and brain
129 tissues. This method can be further used to get the better performance for even very small images. The manual
130 segmentation are done for 10 subjects in Neonatal brain image segmentation in longitudinal MRI studies, it is
131 to be said that manual segmentation can be evaluated for more subjects when decision fusion technique is used.
132 In Construction of Multi-Region-Multi-Reference Atlases for Neonatal Brain MRI Segmentation, large range of
133 data set is adaptable for manual segmentation when decision fusion technique is used to fuse the multiple image
134 segmentation into a single segmentation to bring a final decision. The neonatal brain image when done with
135 manual segmentation gives good result but additionally when decision fusion technique is used it yields a better
136 result. It is to be concluded that manual segmentation with decision fusion yields a good result. All these work
137 can be proceeded to get better result. ^{1 2 3}

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