Segmentation of fetus brain MRI based on K-nn algorithm

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Abstract

The segmentation of MRI of the fetal brain has been emerging as a clinical tool to detect abnormalities during the development of the fetus. Since the brain is still in development, a mixture of regions of white matter, grey matter and transition structures that are related to brain growth are still associated with it. In this work, two versions of the K-nearest neighbour algorithm are proposed as the core method for the recognition of different regions of images; the first one is a refinement of the standard algorithm and the second a reinforcing iterative version of the same method. Both versions are used to identify 3 apriori selected regions — the brain, the intracranial and the remaining part of the fetus body. The effectiveness of the method has been demonstrated in a MR image segmentation that was first pre-processed with digital filters for feature extraction. Contour filters have also been applied to the same image. The results obtained with the proposed segmentation procedure showed better performance than other traditional methods.

1. Image acquisition and pre-processing

Figure 1: *Selected atlas image. The yellow boxes outline the local regions: brain, intracranial space and partial fetal body.*

Digital image processing (DIP) refers to the manipulation of digital images through processing methods able to make it more clear or removing noise and other artifacts. Once the image is uploaded, three square regions of the image are identified as sample sub-images — the brain, the intracranial space and the partial fetal body — whose respective pixels are taken as training data, belonging to the training set (TS). In this work, DIP algorithms are used to provide some local features of the image to the modified K-nn algorithm, which it trying to recognise regions of the image with similar characteristics. The algorithm input are the data features of a circular region around every pixel and the output are the results of two categorical filters: (1) low-pass filters: the mean, the median and the variance; (2) edge or contours operators: Sobel, Canny, Prewitt and the "Laplacian of the Gaussian Operator". Additionally, the variance filter provides for the information variation contained in the local image region, which is important for distinguishing textures and some kind of patterns. The variance is calculated around each pixel as:

$$Var_{ij} = \frac{1}{n} \sum_{(r,s) \in \mathbb{R}_{ij}} \left(I_{r\,s} - \bar{I}_{ij}\right)^2, \tag{1}$$

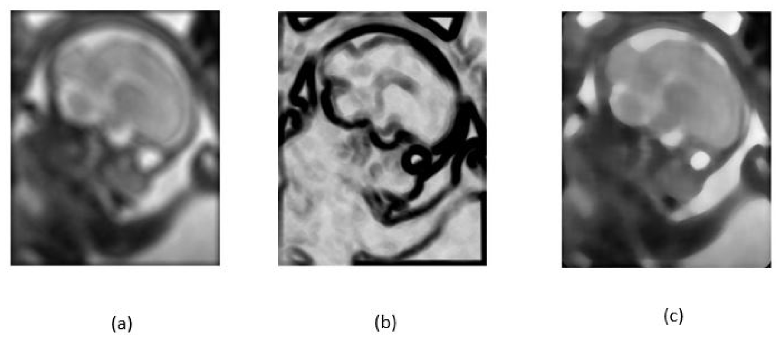

Figure 2: *(a) Media filter; (b) Variance filter; (c) Median filter;*

2. K-nn Algorithm

The K-nn algorithm is a non-parametric method for classification and regression whose input are the closest training examples in the feature space. To understand the k-nn algorithm I gave a simple example shown in the Figure 3 for our algorithm, we have a figure where we want to classify the green point (test sample) as being either blue squares or red triangles. If k=3 (solid color circumference) is assigned to the red triangle class, since there are 2 triangles and appendix 1 square inside the circle. If we change the k to other values, for example 5, the classification will be different is assigned to the blue square class, since we have 3 blue squares and 2 red triangles inside the circle with dashed line

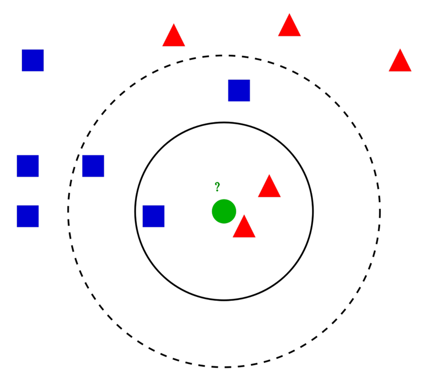

Figure 3:

3. Application of K-nn algorithms and results

In order to obtain results we decided to divide the algorithm into two versions. The first one was a non-parametric way and the second was an iterative way.

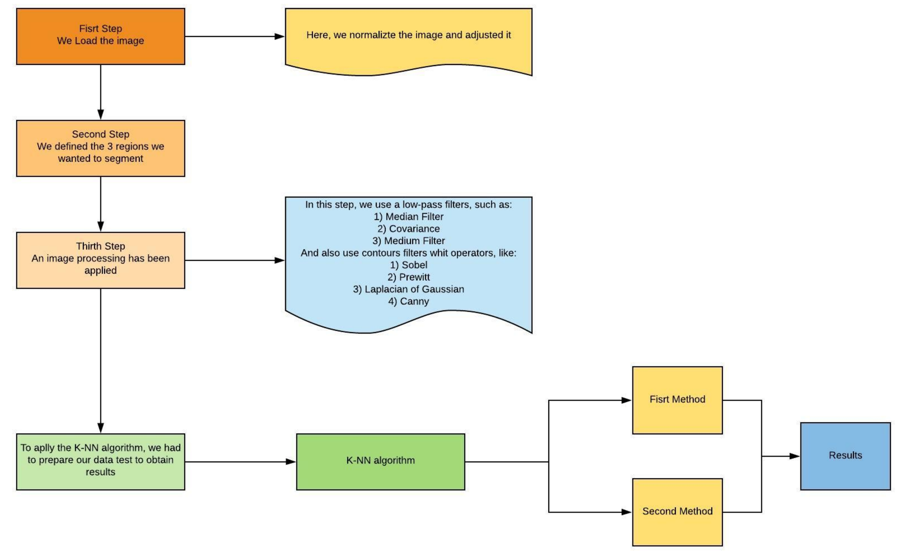

Figure 4:

After we did some alterations the k-nn algorithm gave us a result shown in Figure 5.

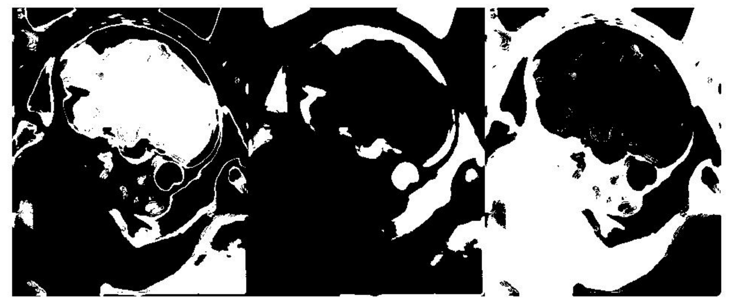

Figure 5:

The results from iterative way are shown in Figure 6.

Figure 6:

4. Conclusions and Future Work

In this work, two versions of the K-nn algorithm were used for segmentation of an fetus brain MRI. The first version is a modified version of the standard algorithm and the second is an iterative version of the first. Both algorithms produced good results to determine sub-regions of the image, although the second one presented a higher confidence value. Besides the good results already obtained, the performance of both versions of the method can be improved by taking other features of the images as input of the K-nn classifier. The presented study illustrates the capabilities of the this type of methods to support obstetricians and general practitioners to assess the fetus and, in particular, its brain.

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