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 Introduction

In the image processing realm, image segmentation (IS) refers to the process of dividing a digital image into multiple regions (sets of pixels), to simplify its representation and facilitate analysis. As a result, a set of regions, or contours, is extracted from the image, where every pixel in the same region has similar characteristics, such as color, intensity, texture, or continuity. In biomedical engineering, the combination of magnetic resonance imaging (MRI) with computational techniques warrants the development of high interest tools for analysis of brain imaging to assist neuro-scientists and general practitioners in the early diagnosis. MRI of the human fetus is emerging as a clinical tool for early detection of brain abnormalities due to its ability to evaluate morphometric measurements of a brain in development and promises a range of new quantitative biomarkers to be used in the clinical evaluation of pregnancy. It is factual that fetus MRI may be corrupted by noise or blurred by the movement of the fetus during the examination. As reported in [4], the anatomy of the developing fetal brain is significantly idiosyncratic, in terms of both geometric and underlying tissue morphology, as it consists of a mixture of white matter, gray matter, and transitory structures related to brain growth. The segmentation of the fetus has been extensively studied by several authors over the years and several methods are described for this type of study. In [5], the construction of an atlas with 10 isotropic images is proposed as a first method. A second method is the construction of a simple atlas based on a segmentation that aims to find the transformation between the atlas and the target low-resolution images. Following a similar methodology, [1] put labels on the atlas to specify different structures of the brain, since these are usually used as a paradigm for automatic segmentation algorithms. In this paper, the fetal brain is segmented through neighbouring characteristics using the K-nn algorithm [2]. It distinguishes different regions automatically as well as structures that are present in the acquired MR images. In our case study, these regions are the brain, the uterus, and partial body. The remainder of the work is organised as follows: Image acquisition and pre-processing are explained in Section 2. The K-nn Algorithm is described in Section 3. The application of the K-nn algorithm and respective results can be found in Section 4. Section 5 concludes the paper and withdraws some directions for future work.

2 Image acquisition and pre-processing

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. Sometimes, DIP is also used to highlight certain characteristics as contours or textures. In this work, test images are downloaded from [3], where one can find several kinds of fetus MRI as the test image shown in Fig. 1. 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". In the processing of the image of Fig. 1, low-pass filters were used to measure the mean properties of a local region of the image, since they produce a smoothed image as result. In particular, median filters can reduce image noise without blurring the image contours. This type of filter is specially suited for removing impulsive noise that appears in limited regions of the image. 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:

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

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

where I_{rs} is the intensity of pixel–(r,s) of the image contained in vicinity $\mathbb{R}_{ij}$ and $\bar{I}_{ij}$ is the mean value of the intensity of all the pixels in $\mathbb{R}_{ij}$. Var_{ij} is the variance of the circular region $\mathbb{R}_{ij}$ centred at pixel–(i,j) and with cardinality n. The result of everyone of these filters is shown in Fig. 2. Regarding contour filters, the best results where obtained with Canny,

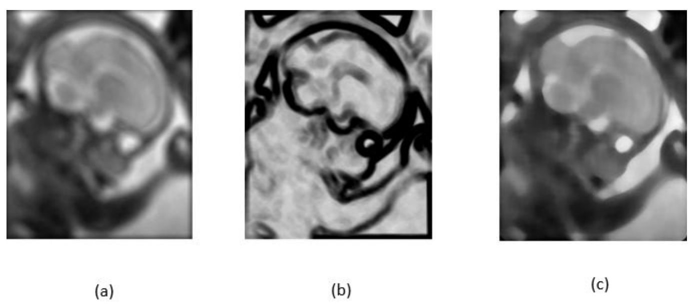

Figure 2: (a) Media filter; (b) Variance filter; (c) Median filter;

since the contours of the brain, intracranial space, and the fetal body are all clearly expressed and highlighted. The image filtered by the Canny operator is one component of the input vector of the K-nn algorithm and is also used to validate the border of the regions of interest identified by our algorithms. The other components of the input vector are the mean (or median) and variance images.

3 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. The output of the algorithm when is used for classification, that is the case here, is an association to one or several classes, i.e., an object is classified by a plural vote of its neighbours and then assigned to the most common class among its closest neighbours. Neighbours are taken from a set of objects for which the class is known, the TS. The algorithm approximates the functions locally, and the entire calculation is deferred until the function is evaluated. Since this algorithm depends on the distance used in the classification task, the normalization of the training data can significantly improve its accuracy. A useful technique may be to assign weights to the neighbours, which gives a larger contribution of the closest neighbours to the average. In K-nn algorithm, K is a user-defined constant of the number of nearest neighbours. When $K = 1$ the algorithm is known as the nearest-neighbour algorithm. The training examples are vectors in a multidimensional feature space, each with a class label. The training phase of the algorithm consists only in storing the features' vectors and class labels of the training samples. Suppose we have a set of n pixels, everyone with a d-dimensional feature vector, $X_i \subset TS \in \mathbb{R}^d$, $i = 1, \cdots, n$. These are classified and partitioned into c–classes, where Y_i is the class label value of the i^{th} sample, $Y_i \in \mathrm{N}_1^c = \{1, 2, \cdots, c\}$. An unlabelled vector is classified by assigning to it the label which is most frequent among its K nearest neighbours belonging to TS. Consider some norm $\|\cdot\|$ on $\mathbb{R}^d$, e.g. Euclidean distance, Hamming distance, Manhattan distance or Minkowski distance, and a non-classified pixel of index k with features vector $X_k \subset US$ (Unlabelled Set). Hence, let a sequence of ordered pixels of TS, such that $\left\|X_{I(1)} - x_k\right\| \leq \left\|X_{I(2)} - x_k\right\| \leq \cdots \leq \left\|X_{I(K)} - x_k\right\|$, where I is the list of indices of the K nearest neighbours training pixels. The classification of point k is done by the majority vote of its K neighbours. The score value is $V_{ik} = \sum_{j=1}^{K} u_{i,I(j)} w_{I(j),k}$, where k-point belongs to the i^{th} class. u_{ir} is the membership value of the r training point that belongs to the i^{th} class (e. g. $u_{ir} = 1$ if $Y_r = i$ and $u_{ir} = 0$ otherwise). w_{jk} is the weight of every j^{th} nearest-neighbours. Finally, the class with most votes is taken as the prediction, i.e., $Y_k = i$ when $V_{ik} > V_{jk}, \forall i \neq j$. The quality of the classification of the unmarked samples X_k will be better if the result of the vote is concentrated in a certain class, by expressive majority voting. This measure is the *certainty belief factor (CBF)*: $S_{ik} = V_{ik}^{\alpha} / \sum_{j=1}^{c} V_{jk}^{\alpha}$, where α is a shape parameter. This measure can be see as a confidence value of the classification process. Values of S close to 1 reveal high level of confidence and express goodness of the classification.

4 Application of K-nn algorithms and results

Two distinct versions of K-nn algorithm are implemented. First, the segmentation of the brain image is done in a non-iterative way by a plain K-nn algorithm. In a second version (RK-nn), an iterative version of the algorithm reinforces the classification process. In every iteration, the pixels with lower CBF are rejected and not classified, and pixels with higher S-value are added to the TS in the next iteration. Also, TS pixels with lower mean weight values are discarded from the TS. Then, at the new iteration, the non-classified points are subject to a new classification process. Both algorithms were tested on the same image and training data, with $K = 50$. The components of the input vector X are the mean and variance intensity of a circular region centred in the each pixel and the value of the contour filter. For the RK-nn, the threshold value for inclusion or rejection to/from TS are, respectively, 0.8 and 0.2.The results obtained with the first version are shown in Fig. 3: brain (1), intracranial space (2) and partial fetal body (3). All pixels of the image are classified into these three classes. However, pixels that belong to the border regions or edges of structure have low levels of CBF. In the second version, the method

Figure 3: Non-iterative version: Segmentation into (1) brain; (2) intracranial space;(3) partial fetal body.

terminated at the 3rd iteration. For the specified threshold values, 50% of the pixels were well classified in first iteration, 12.1% in the second and the remaining pixels in the last one. The results are shown in Fig. 4, where white zones represent high membership value of the image region to the class. Black regions represent no pixels in the class. With this version, the confidence results of the classification process improved around 20% for the well classified pixels.The results obtained with both versions of the algorithm were compared with the K-mean clustering algorithm and other K-nn algorithms and showed better confidence results.

Figure 4: Iterative version: Segmentation into 1) brain; (2) intracranial space;(3) partial fetal body.

5 Conclusion 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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