A Texture Based Adaptive Speckle Suppression Method for Ultrasound Images of the Neonatal Brain

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I. Introduction

White matter damage of the neonatal brain, in its focal or diffuse variant, is found in 20 percent to 50 percent of very low birth weight infants (<1500g). Focal WMD can lead to the formation of cysts in the brain (cystic periventricular leukomalacia), which predicts spastic di- and quadriparesis and sometimes cognitive dysfunction and mental retardation. Generally WMD reveals itself in an ultrasound image as a "zone of increased echodensity" (i.e. a typical kind of "white cloud"), called a "flare". The visual interpretation of ultrasound images of the neonatal brain for making an unambiguous and correct diagnosis of WMD by means of the presence of flares, however, is often hindered by the presence of speckle noise. In this paper we aim to introduce an adaptive filter, which reduces the speckle noise in ultrasound images of the neonatal brain significantly in the healthy tissue, while, at the same time, it leaves the areas infected by WMD (the "flares") untouched, thus serving as an aid for the sonologist to make a more accurate diagnosis, by distinguishing clearly the ill tissue from the healthy ones.

To achieve this goal, the presented filtering technique takes into account first and second order local statistics of the image in order to adapt its strength in the various regions.

We have found that infected areas can be distinguished from healthy ones by considering the mean grey-value and the contrast. In [3] similar results were obtained for ultrasound images of the prostate. In II.A the preliminary results of this research are presented. Using these, the filter works on a combination of the two parameters mentioned above.

In II.B the filter itself is explained in detail. First the original image is converted to an image, in which the grey-values are independent of the scanner settings selected by the sonologist, by means of a compensation algorithm, as introduced in [1]. A region growing procedure, in which the region growing is controlled by grey-value limitations, segments this compensated image [2], [5], [6]. Then in every region the contrast and mean grey-value are calculated, and a speckle reduction algorithm, consisting of a complementary hulling technique introduced in [4], is applied iteratively, where the number of iterations depends on the parameters calculated. As the various tissues are characterised by the parameters mentioned, we achieve in this way that the speckle noise is suppressed in the healthy tissues in the image, while details, especially in the WMD zones, are maintained.

In III. the results are compared with two classical speckle suppression filters, namely the Lee [7] and the Frost filter [8], as well as with another adaptive speckle suppression filter, which is also based on a region growing procedure, combined with filtering dependent on local statistics [2].

II.A Preliminary Results

16 Images of children without WMD, and 32 images of children with WMD are investigated. All these images where transformed by the compensation introduced in [1], and a rectangle of 32x30 was selected in all of them in the periventricular zone. Within this rectangle the mean grey-value and the cooccurrence matrix were calculated. From this cooccurence matrix several parameters (like contrast, uniformity, entropy, inverse difference moment) were calculated.

The results are scatter plotted in figure 1. The separate cluster in the left bottom corner represents the values of the images of the healthy children. The rest are the values of the images of the children with WMD. Deciding the limits manually, we conclude that

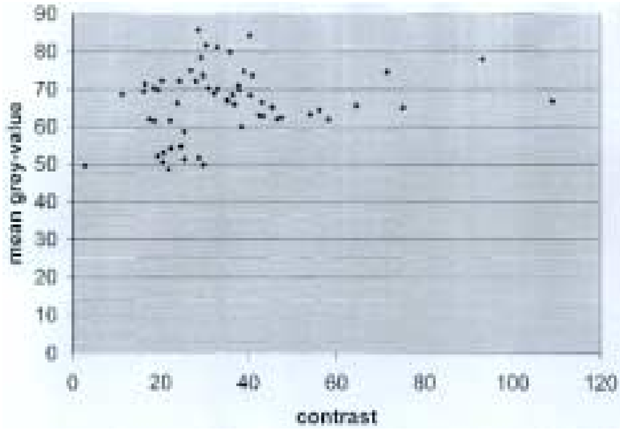

Figure 1: Result of the investigated 48 images

a mean grey-value of less than 65 together with a contrast of less than 35 mean that the child is healthy. In all other cases it suffers from WMD. (A complete research and an article about it are still in progress).

II.B The Filter

As indicated in figure 2, the overall procedure of the filter can be described in five steps:

1) First, out of the original image a “compensated image” is constructed, with the compensation algorithm introduced in [1].

2) Then, by applying a mean filter to this compensated imaged, a “blurred compensated image” is made.

3) This blurred image is segmented using a region growing procedure, in which the grey-values of the pixels are used as a quantitative measure to control the shape of the regions grown.

4) Now we consider the same segments, but in the compensated image. We calculate the mean grey-value, and the cooccurrence matrix of each segment. With this cooccurrence matrix you can calculate several texture dependent parameters. We calculate the contrast.

5) Again we consider the same segments, but now in the original image. Here we apply the so-called Crimmins Filter in the regions iteratively; the number of iterations is dependent on the contrast and the mean grey-value calculated in step 4).

We shall describe and motivate each step in detail:

1) Construction of the “Compensated Image”: When making an ultrasound image of the neonatal brain, the sonologist can select various scanner settings, like the power (the amplitude of the emitted waves), the gain (overall amplification of the received signal), the depth (the depth on which the emitted ultrasound bundle is focussed), the Time Gain Compensation (different amplifications of the reflected signals from different depths) etc. Since we want the filter to distinguish between various tissues, and want to use first en second order statistical parameters for that (which are obviously influenced by these scanner settings), we have to construct a “standard image” first; an image which is independent of those scanner settings. In [1] extensive study of this problem has been made, and a compensation algorithm which constructs such kind of standard image is described.

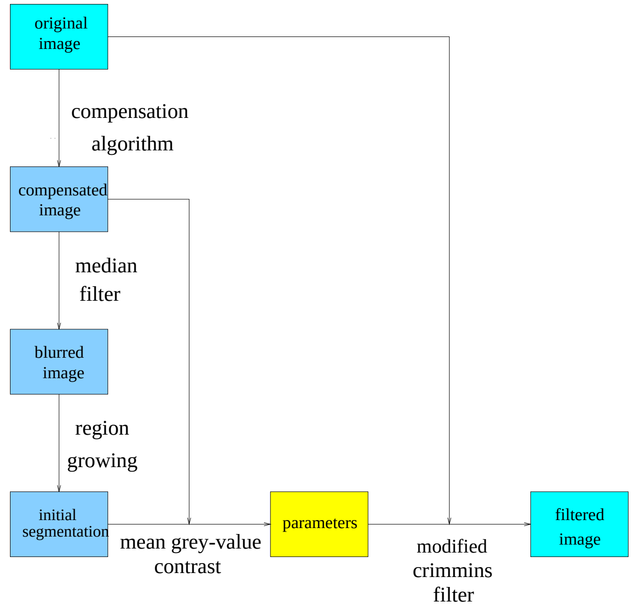

Figure 2: The structure of the filter

2)Application of a Mean Filter: Because we are going to apply a region growing procedure based on the grey-value of the pixels, we want to get rid of the sharpest speckles first. Otherwise the regions will “grow around” these speckles. To achieve this, we apply a mean filter to the compensated image. By means of visual inspection, an 11x11 kernel turns out to reduce the speckle enough for this purpose, while at the same time it does not blur the image too much.

3) Region Growing Procedure: In our filter, the grey-values of the compensated image are used as the quantitative measure to obtain a region for each image pixel. All pixels are checked from left to right, from top to bottom. The first pixel is taken as the initial seed pixel, whose grey-value is $\alpha_{(i,j)}$. Then its eight neighbouring pixels are considered. Whenever the grey-value of one of these pixels differs less than a fixed number $\Delta\alpha$ from $\alpha_{(i,j)}$, and the pixel has not been classified in a different region already, then it is added to the region under construction. Here $\Delta\alpha$ (the *toler-*

ance) is one of the adjustable parameters of the filter. In our experiments a tolerance of $\Delta\alpha = 4$ gave the best results.

After that, these new members of the region are checked in the same way, the grey-values are still compared with $\alpha_{(i,j)}$, etc. In a separate array, we keep track of which pixels already belong to a region.

So, after a region stopped growing, (because all surrounding pixels already belong to other regions or because none of the adjacent pixels has a grey-value that falls within the accepted range of tolerance), the first next pixel which does not belong to one of the regions already formed, is taken as a new seed pixel, and the same procedure is repeated.

In short, to test whether a pixel (m, n) belongs to the homogeneous region of a seed pixel (i, j), the following must be satisfied:

- Pixel (m, n) is "connected" to pixel (i, j)
- $|\alpha_{(i,j)} - \alpha_{(m,n)}| < \Delta t$
- Pixel (m, n) does not belong to a region, which has already been formed before.

4) Calculation of the Various Parameters: The mean grey-value is calculated for every region in the compensated image. Furthermore, for every region in the compensated image, a cooccurrence matrix is calculated in the following way: First we define a 256x256 zero-matrix A. We consider each pixel (i, j) of the region, and consider its right next neighbour $(i, j+1)$. If pixel (i, j) has grey-value a, say, and pixel $(i, j+1)$ also belongs to the region under consideration, and has grey-value b, say, then coefficient (a, b) of A is increased by 1. Finally, when the whole region is scanned, A is divided by the sum of all of its coefficients. As a result, the coefficient $A_{i\ j}$ represents the chance that you will find a "grey-value transition" from grey-value i to grey-value j, if you consider pairs of neighbouring pixels (which both belong to the region under consideration). The reason we consider the right neighbouring pixel in constructing the cooccurrence matrix, is that it is also done this way in the measurements for distinguishing the healthy from the ill tissues.

Now the cooccurrence matrix A has been calculated, the contrast c can be defined as follows:

$$c = \sum_{i,j=0}^{255} (i-j)^2 A_{i+1\ j+1}$$

5) Smoothing Operation: The actual smoothing procedure is applied to the original image. We do this, because we intend to keep the overall grey-value, especially in the regions that are not smoothed at all, as much in the original state as possible. (Since the filter is designed to be used for visual inspection, we want the areas, which have been brightened or darkened by the gain settings selected by the sonologist, to stay like that). The filtering itself is performed by the Crimmins filter [4]. This filter works in four consecutive steps: North South adaptation (NS step), East West adaptation (EW step), Northeast Southwest adaptation (NE-SW step), Northwest Southeast adaptation (NW-SE step).

NS step We work with two images; the second image is an exact copy of the original image. Every pixel in the original image is scanned. First we check if the grey-value g of the pixel under consideration is smaller than that of its northern neighbour or that of its southern neighbour. If that is the case, then the grey-value of the pixel at the same position in the second image is increased by 1. Then we check if the grey-value g of the pixel under consideration is higher than that of its northern or that of its southern neighbour. If so, then we decrease the grey-value of the pixel at the same position in the second image by 1. After having scanned all pixels of the image, the second image thus constructed is used as the input image for the next step.

EW step, NE-SW step, NW-SE step Analogous to the NS step, but now the grey-value of the pixel under consideration is compared with respectively the Eastern and the Western neighbour, the northeastern and southwestern neighbour, the northwestern and southeastern neighbour.

The reason why this technique works on speckle is the following. Suppose you have a homogeneous background, with one isolated extremely light (or extremely dark) pixel on it. By applying this filter once, the grey-value will be decreased (increased) by 4. The less isolated the pixel is, or the less its grey-value differs from the background, the less its grey-value will be influenced. Speckle seldom appears as isolated pixels, but it does appear as small thin lines. Since the filter darkens the pixel, if you are in the situation that the neighbouring pixel on one side has the same value and on the other side it is darker, these speckles will disappear as well. A disadvantage of this method is that it blurs edges, so in applying it multiple times, one has to balance between speckle suppression and edge preservation.

We have tested this on several images; if you apply this filter more than 30 times (just on the whole image), then the result is almost uniformly grey. So

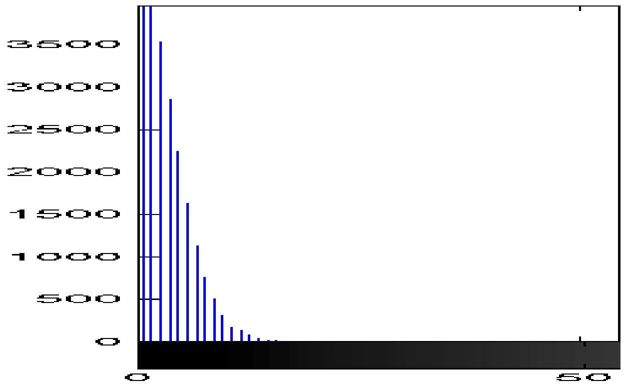

Figure 3: Positive difference values

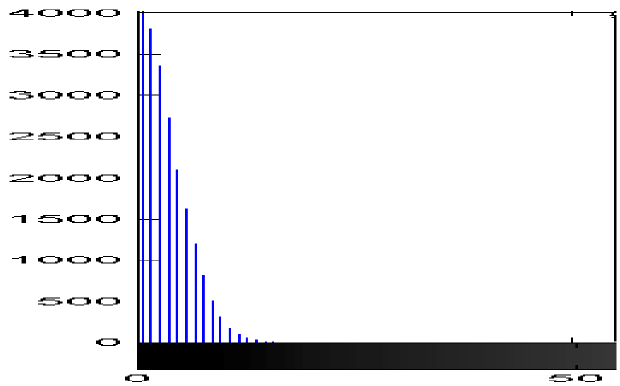

Figure 4: Negative difference values

not too many iterations should be needed to suppress the speckle. Since the grey-value of a pixel can be change by 4 at most in each iteration, this implies that the grey-value of the noise pixels should not differ too much from the “background”. To check that this holds for the images we investigated, we selected a homogeneous region in a typical image we investigated, applied a mean-filter with a 9x9 kernel to it, subtracted the result of this from the original image, and drew two histograms of this difference: one of the positive values and one of the negative values. They are presented in figure 3 and figure 4. As one can see, far most of the values lie between -12 and 12, which corresponds to 3 iterations in the case of an isolated pixel, 4 in the case of a thin line.

Back to the question how we apply this technique in a specific region. When applying the filter, we can adjust four parameters:*bottomcontrast*, *topcontrast*, *maximumnumberofiterations* (in our case 7), and *limitgrey-value* (in our case 70). So the number of times the filter is applied to the region (and thus its smoothing strength) is determined as follows:

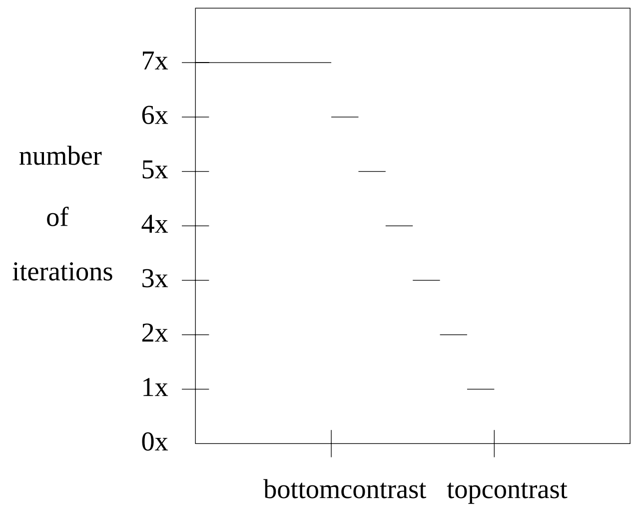

Figure 5: Determining the filterstrength

If the mean grey-value is higher than *limitgrey-value* or the contrast is higher than *topcontrast*, then we do not filter at all.

If the contrast is lower than *bottomcontrast* and the mean grey-value is lower than *limitgrey-value* then we filter *maximumnumberofiterations* times.

When *bottomcontrast* < contrast < *topcontrast*, we apply the filter

$$\left\lfloor \frac{(\text{contrast} - topcontrast) * maximumnumberofiterations}{(bottomcontrast - topcontrast)} \right\rfloor$$

number of times.

So,the number of iterations is dependent on the contrast like shown in figure 5.

III. Simulations and Comparison

The performance of our filter is investigated on a tissue image, together with another recently reported method [2], employing image local statistics in filter adaptation. It is also compared with two classical speckle suppression filters, namely the Lee and the Frost filter [7][8].

Before presenting the simulations and the comparison, we will outline here how the filter presented in [2] (the ASSF filter) works.

- For every pixel (i, j), the signal-to-noise ratio $\gamma_{i,j} = \frac{\sigma^2_{i,j}}{\mu_{i,j}}$ is calculated in an 11x11 window around this pixel.
- The statistical similarity criteria $\beta(\gamma_{i,j}) = a + be^{-c\gamma_{i,j}}$, to be used as the region growing bounds, are calculated. Here a, b and c depend on the

characteristic value of signal-to-noise ratio of the tissue to be filtered and the desired smoothing level.

- For every pixel:

  - Grow the homogeneous region; to test whether a pixel (m,n) belongs to a homogeneous region of a seed pixel (i,j), the following must be satisfied:

$$\text{Pixel } (m,n) \text{ is “connected” to pixel } (i,j)$$

$$\alpha_{i,j} - \beta(\alpha_{i,j}) < \alpha_{m,n} \leq \alpha_{i,j} + \beta(\alpha_{i,j})$$

$$\sqrt{(m-i)^2 + (n-j)^2} \leq D_b.$$

  - Calculate the mean/median of the pixels in the grown region.

  -Output the result.

- For every pixel:

  - Merge the neighbouring regions: Let $Z_{i,j}$ be the region of the seed pixel (i,j), and let $N_{i,j}$ be the number of pixels in $Z_{i,j}$. If $N_{i,j} \leq K_b$, then $Z_{i,j}$ is not involved in the merging procedure. Otherwise, each region $Z_{m,n}$ neighbouring the region $Z_{i,j}$ is merged to the region $Z_{i,j}$ if the following is satisfied:

$$\mu_{i,j} - \Delta\mu \leq \mu_{m,n} \leq \mu_{i,j} + \Delta\mu \text{ and } N_{m,n} > K_b.$$

  Here $\Delta\mu$ and K_b are positive constants and represent the bounds for the grey-value and the number of pixels respectively.

  - Update the outputs by taking the mean/median of the pixels in the merged regions.

Both the Lee and the Frost filter do not use a region growing procedure, but work with a fixed sized kernel instead. We included them, because they are well known “standard” speckle suppression filters.

Simulation and comparison

The performance of each filter that is outlined in the previous subsections is evaluated qualitatively on an ultrasound image of the neonatal brain. The results are shown in the figures 7-10.

As can be seen from these plots all filters effectively reduce the speckle. The ASSF filter and the propsed method though, leave the original contrast better intact than the Lee and the Frost filter do. Furthermore our method is considerably faster than ASSF, because of the following reasons:

Figure 6: Original image

Figure 7: Lee filter

- Since the growing in our method is dependent on the grey-values of the pixels only, we do not have to calculate a signal-to-noise ratio for every pixel first.
- We use a fixed range in which the grey-value may differ, so we do not have to make a(computationally intensive) look-up table for β.
- The regions we grow do not overlap. Henceforth there are far fewer regions to be grown.
- We have no merging procedure.

IV. Conclusion

In this paper we presented an adaptive speckle suppression filter, which filtering strength is dependent on the local mean-grey value and contrast. The results have been compared to several other speckle suppression methods. In a comparative study with three oth-

Figure 8: Frost filter

Figure 9: ASSF filter

er filters, the proposed method outperformed in suppressing the speckle in healthy tissue, while leaving the areas infected by WMD untouched. Doing so, it is considerably faster than another adaptive filter we investigated in our study. Apart from serving as an aid to the visual diagnosis of the sonologist, the method presented could also serve well as a pre-processing step in segmentation of ultrasound images.

References

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Figure 10: Proposed method

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