A Medical Feature Enhancing New Denoising Technique for Ultrasound Images

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Abstract

20% To 50% of the neonates with a very low birth weight (VLBW:<1500g) is suffering from leukomalacia (White Matter Damage) at birth. Leukomalacia, especially in the early stage of its development, is visible in ultrasound images as "white clouds" (so-called "flares"). The gravity of the damage can be determined from the shape, the area, and the internal texture of those flares.

In this paper we introduce a new speckle suppression technique that takes into account tissue classifying parameters. The individual speckles are located, and exploiting our knowledge on the tissue classifiation determines whether the speckle is noise or a medically relevant detail. If it is noise, then it is removed.

We conclude with showing that applying an active contour after the proposed technique yields a segmentation much closer to that of an expert.

1. Introduction

Ultrasound imaging of the neonatal brain since birth is routine medical practice nowadays. These images can reveal several pathologies, like infections, asphyxia, matrix bleedings, etc. In this article we focus on leukomalacia. Leukomalacia, in its focal and diffuse variant is found in 20% to 35% of the neonates with a very low birth weight (VLBW: < 1500 g.) It is typically visible in ultrasound images as "white clouds" (so-called "flares"). Three features are most important in determining the gravity of the damage: the shape and the area of the flares, and the presence of "accents", i.e. particularly bright speckles which are bigger than usual, located within the flares, [1, 2]. In figure 1 we see an ultrasound image of an infant brain affected by leukomalacia. The "white clouds" are the flares (see the white arrows); the long thin arrows point to some "accents" in the flares, the presence of which suggest this to be a very serious affection.

At present, the diagnosis of leukomalacia still solely dependends on the visual inspection and subjective interpretation by an expert. In [3] the limits of of this procedure are explained. As a step towards a computerized method and as an aid to the visual diagnosis of the neonatologist, we present in this article a new speckle suppression method, which suppresses the speckle in the healthy tissue, while it leaves the areas affected by leukomalacia untouched. Thus processed, we gain the advantage that using a *GVF-snake* [4, 5] on the resulting image in order to delineate the flares in a semi-computerized way yields a segmentation much closer to that of an expert than when the same procedure is followed on the unprocessed image.

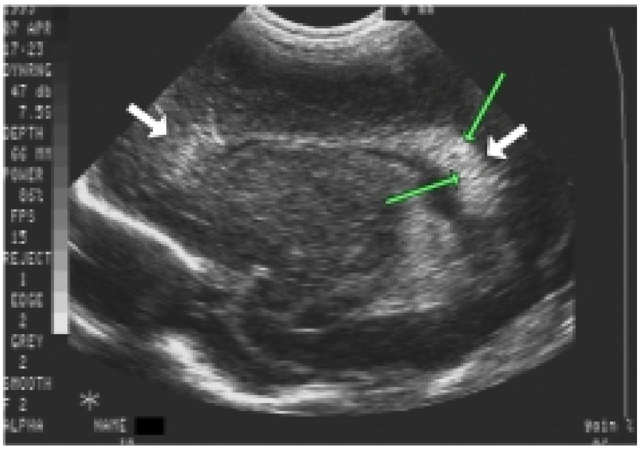

Fig. 1. **Flares and "accents".**

2. Texture parameters

First we describe an experiment that we performed to obtain the parameters, related to texture classification. The results of this experiment provide statistics that enable us to characterize the different tissues the filter is designed to distinguish.

When making an ultrasound image of a neonatal brain the neonatologist can select various scanner settings, like the power (the amplitude of the emitted waves), the gain (the overall amplification of the received signal), the Time Gain Compensation (different levels of amplification for different depths) etc. Since we want to *quantitatively* compare images with respect to first and second order texture statistics, (which are obviously influenced by these scanner settings), we have to construct "standard images" first, which are independent of those scanner settings. This problem has been studied extensively in [3], and a compensation algorithm that constructs such a standard image is described. In figure 2 the compensated version of the image of figure 1 is shown.

We considered 48 images of neonates, all of which were classified by the neonatologist as certainly ill (i.e., suffering from leukomalacia) or certainly healthy. All of these images were processed by the compensation algorithm first. In the resulting 48 compensated images we selected a rectangle of 30×30 pixels at exactly the same spot (near the so-called periventricular zone) as shown in figure 2. According to the neonatologist, a flare is present in that region, if the infant suffers from leukomalacia.

Within the rectangle we calculated several parameters including the mean grey-value and the contrast. This "contrast" is defined as follows: let r be a region in the image like, for instance, the one shown in figure 3. Denote by A_{kl} the number of pairs of adjacent pixels within r with grey-values k and l respectively. (In our example $A_{kl} = 3$).

Now we define the contrast γ_r of r as:

$$\gamma_r = \frac{\sum_{k,l=0}^{255} (k-l)^2 A_{kl}}{\sum_{k,l=0}^{255} A_{kl}}.$$

The contrast is a measure for how many grey-value transitions there are in the region under consideration; the more adjacent pixels with a big difference in grey-value there are in r, the higher the contrast γ_r is. In practice, the contrast is calculated by means of the *cooccurrence matrix* [6–8].

The mean grey-value and the contrast turn out to be distinctive in determining whether the area under consideration is ill or healthy. A scatter plot of the results is shown in figure 4. The separate cluster in the bottom left corner indicates that a mean grey-value of less than 67, and a contrast of less than 35 means that the tissue within the area is healthy, otherwise it is ill. Similar results, but for ultrasound images of the prostate, were obtained in [6, 9, 10].

3. Filter

The core of the method is to first identify the individual speckles. They are located by means of their higher grey value, and then a region growing procedure is applied to isolate them. (The detailed description of the method follows below). For each speckle found this

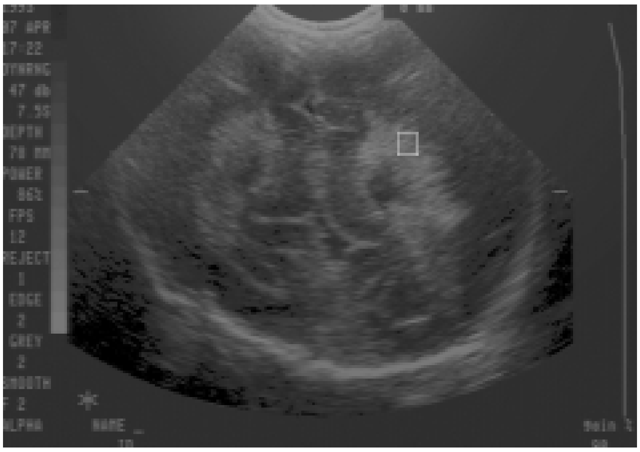

Fig. 2. **The specific rectangle (simulation).**

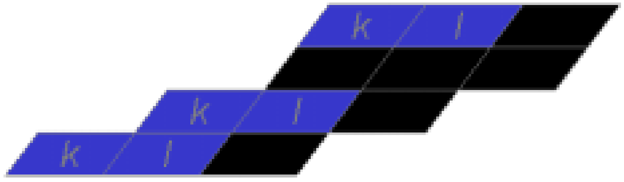

Fig. 3. **A region.**

way, it is checked -using the classification of the different kind of textures- whether the speckle is located in healthy tissue or not. If it turns out that the speckle is located within healthy tissue, then it is noise, and hence removed, otherwise it is left untouched. This way the medical features of the flares (shape, area, and any accents) are well-preserved.

The detailed description of the method is as follows. Three datasets serve as the input for the filter: the original image as it is produced the ultrasound machine, the compensated image, and an empty image, in which we keep track of the speckles that are grown.

Now we follow the following procedure:

1) Let Γ be the global maximum grey value in the image. Choose a pixel (i, j) with grey value Γ. This pixel serves as a seed pixel for a region procedure, controlled by the grey value of the pixels. As a threshold T, we set $T = 23$. In short: a pixel (m, n) belongs to the region of a seed pixel (i, j), when the following are satisfied:

- Pixel (m, n) is "connected" to pixel (i, j),
- $\alpha_{(m,n)} > \alpha_{(i,j)} - T$,
- Pixel (m, n) does not belong to a speckle which has already been grown, or to the border of one of those speckles (i.e., (m, n) is also not adjacent to one of the earlier grown speckles). In this way we isolate one single speckle Σ.

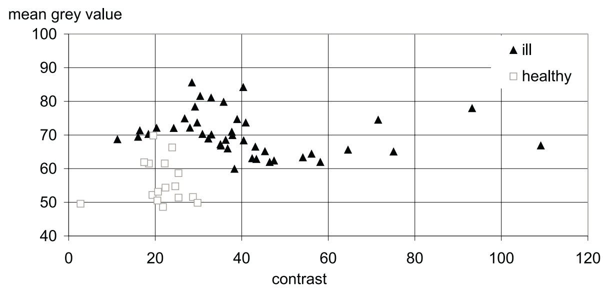

Fig. 4. **Results of measurements.**

2) Next we determine the centre of gravity g_Σ of Σ, and consider the same position as g_Σ in the compensated image. Take a square of 30×30 pixels around g_Σ (in the compensated image), and calculate its mean grey value μ_Σ and its contrast γ_Σ.

3) If $\mu_\Sigma > 67$ or $\gamma_\Sigma > 35$, we conclude that the speckle is located in an affected part of the brain tissue, and hence the speckle Σ need not be removed. We go back to 1) and grow the next speckle. Note that from now we no longer take Σ or any pixel adjacent to it (its "border") into consideration. (So Γ will now be the maximum grey value of all pixels in the image except those in Σ and its border).

4)If $\mu_\Sigma \leq 67$ and $\gamma_\Sigma \leq 35$ then the pixel is located in healthy tissue, and hence is considered noise that should be removed. We calculate the mean ν_Σ of the grey values of all the pixels adjacent to Σ (we call this the "border" of Σ), and give all pixel of Σ the value ν_Σ. In this way actually "cut off" the speckle.

5) We repeat the whole process (from step 1), in which we disregard Σ and its border. We continue doing this until the maximum Γ becomes smaller than a fixed lower threshold Λ. We took $\Lambda = 80$.

Both T and Λ are adjustable parameters of the filter, and are dependent on the exact qualities of the ultrasound machine.

In figure 5 the speckles, as they are found by step 1), are indicated. To achieve this result, we applied the technique as described, but, instead of filtering the speckles, we coloured them blue.

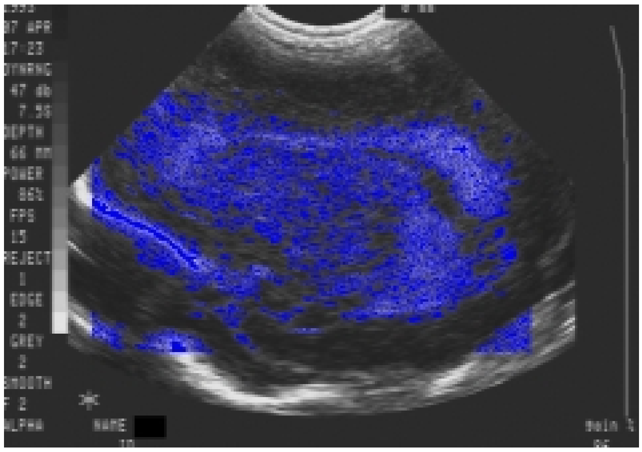

Fig. 5. **Speckles as found by proposed technique.**

Fig. 6. **Original image.**

4. Experimental results

We applied the proposed method on the image in figure 6. The result is shown in figure 7. In figure 8 we can find the manual delineation performed by an expert. First of all, we can see that visually the ill regions are much more distinguishable in the processed image. The speckle is much removed in the healthy tissue, while details are kept, and the affected tissue together with its internal structure is well-preserved. In figure 10 we see the result of segmenting a flare on the original image with a GVF-snake, starting from the position in figure 9. In figure 11 the result is shown on the filtered image, starting from the same position as in figure 9.

5. Conclusions

In this paper we introduced a new speckle supression technique for medical ultrasound images, which takes into account the local speckle statistics as well as quantitative, tissue characterizing, texture parameters. In our examples, that we achieved good speckle suppression in the healthy areas, while at the same we preserved important medical details in the affected areas. Visual inspection of the result shows clearly that the affected areas are better distinguishable,in particular the shape, area, and inner texture, which could seve as an aid in the diagnosis.

Fig. 7. **Filtered image.**

Fig. 8. **Delineation by expert.**

To validate our results, we segmented an affected area with a GVF-snake in the processed as well as the unprocessed image, thus using the filter as a preprocessing step for segmentation. Comparison of the results with the manual segmentation of an expert reveals a considerable improvement of the performance of the active contour when the image is processed with the proposed method.

Finally the method is not computationally intensive. On Pentium II the filter procedure takes 24 seconds for an image of 722x506 pixels. (This is the size os the image in figure 7).

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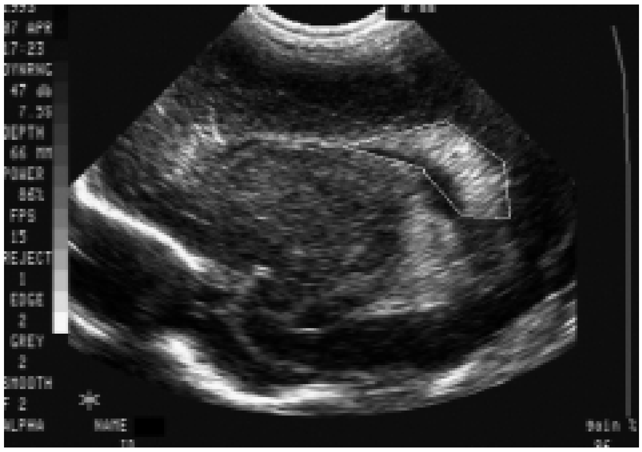

Fig. 9. **Initial state active contour.**

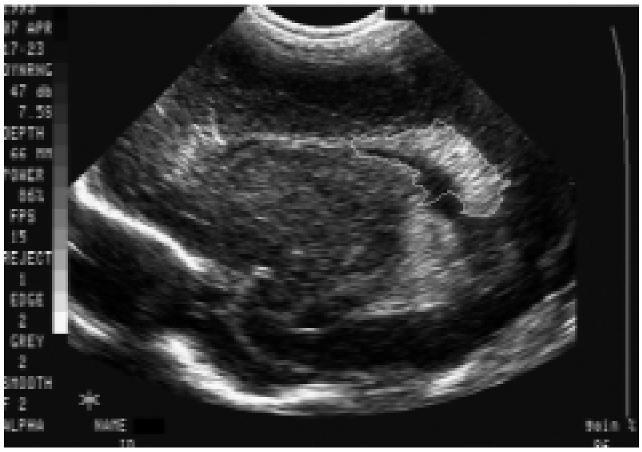

Fig. 10. **Final state active contour.**

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Fig. 11. **Final state in filtered image.**

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