A NEW FILTERING METHOD FOR ULTRASOUND IMAGES INCORPORATING PRIOR STATISTICS CONCERNING MEDICAL FEATURES

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ABSTRACT

20 To 50 percent of the neonates with a very low birth weight (VLBW:< 1500 g) suffer from White Matter Damage (leukomalacia). Nowadays the diagnosis of WMD is still solely dependent on the visual interpretation by an expert. A need for a (semi-) computerized way of segmenting the affected regions, in order to make quantitative measurements as an aid to the subjective diagnosis, is felt. Applying active contours for this purpose, is a classical approach. The performance of active contours for this purpose, however, is heavily deteriorated by the presence of speckle noise.

In this paper a new filter, taking into account local statistics in the image, is proposed; it removes a significant amount of speckle noise in the healthy parts, while it makes the areas affected by WMD more uniform, thus severely improving the performance of the active contour. The results show that applying an active contour after the proposed technique yields a segmentation much closer to that of an expert.

1. INTRODUCTION

In this article we address the problem of suppressing speckle noise in medical ultrasound images. Removing speckle noise from ultrasound images is especially difficult, since this kind of noise is image dependent. The problem is to remove the noise without losing valuable image data. Several techniques for removing speckle noise from ultrasound images have been developed. They can be divided into two classes:

1. Techniques that are applied directly in the original image domain like the Lee [1] and the Frost [2] filters,

2. Techniques that are applied in the wavelet domain like the technique developed by Malfait and Roose [3], which is a universal filter, and the technique proposed by Sattar, Floreby, Salomonsson and Lövström [4], designed especially for speckle noise reduction.

None of these methods take into account prior knowledge concerning the speckle statistics in healthy and ill regions. This makes them less suitable to enhance specific (desired) medical features in the image.

In this paper we focus on ultrasound images of the neonatal brain. White Matter Damage (WMD) is visible in an ultrasound image of the neonate's brain as “zones of increased echo-density” (so-called “flares,” see figure 3). By measuring local texture parameters in the image, we succeeded in distinguishing the areas affected by WMD from the healthy ones. In this article we describe a filter which takes into account these local texture characteristics, and, exploiting our prior knowledge on tissue characterization, suppresses the speckle in the healthy areas, and makes the areas affected by WMD more uniform.

The filtered images obtained by this new method can serve as an aid for visual interpretation. Our goal in this paper, though, is to use it as a preprocessing step for the segmentation of the flares with an active contour. In an image, we will segment a flare by means of a *GVF-snake* [5,6] before and after applying the proposed filter to it. After that we compare the results with the manual segmentation of an expert, and conclude that the performance of the active contour improves considerably by the filtering of the image.

2. DISCRIMINATIVE PARAMETERS

We investigated 48 ultrasound images, all of which had been classified by a neonatologist as either certainly ill (i.e., suffering from WMD), or certainly healthy; 16 of these images were from a healthy child, and 32 from a child suffering from WMD. 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 amplification of the received signal) etc. Since we want to make comparative measurements between the images with respect to first and second order

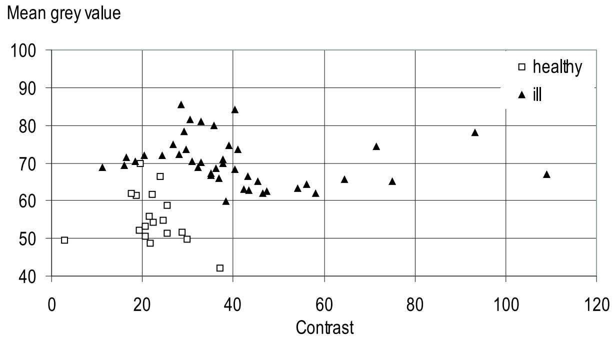

Fig. 1. Results of measurements.

statistics (which are obviously influenced by these scanner settings), we have to construct a "standard image" first, which is independent of those scanner settings. This problem is studied extensively in [7], and a compensation algorithm that constructs such a standard image is described.

So first we processed all images by the compensation algorithm described in [7]. In all of the images we selected a rectangle of 30x30 pixels at exactly the same spot (near the so-called periventricular zone). According to the neonatologist, there will certainly be a "zone of increased echodensity" on that place, if the infant suffers from WMD. 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. Denote by A_{kl} the number of pairs of adjacent pixels within r with grey-values k and l respectively. Now we define the contrast γ_r of r as:

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

In practice, the contrast is calculated by means of the *co-occurrence matrix* [8–10].

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 1. 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 [8, 11, 12].

3. THE NEW METHOD

The method proposed in this paper is based on analysing local texture characteristics in the image. As said, the goal of our technique is to suppress the speckle in the healthy regions, while at the same time the affected regions are made more uniform. It works as follows:

First we we make a copy of the compensated image and apply an 11x1 median filter on it. Now in the compensated image a region r is grown around a seed pixel, where the growth is controlled by the grey-value of the pixels in the median filtered image: if the seed pixel in the median filtered has grey-value α, all "connected" pixels with grey-value β with $|\alpha - \beta| < 3$ belong to r. It is because of his region growing procedure that we work on the median filtered image: we want to get rid of the sharpest speckles without blurring the image too much; otherwise the regions will "grow around" these speckles. Finally within the grown region (in the compensated image) the mean grey-value μ_r and the contrast γ_r are calculated.

For suppressing speckle on the one hand, and making an ill area more uniform on the other hand, we use two different procedures, which we call the "darkening procedure" and the "lighting procedure" respectively. Both can be applied iteratively to tune the strength of their effect.

The idea behind performing the lighting procedure to make an affected area more uniform, is to light the dark areas between the speckles. Since the speckles in the same radian from the transducer are all oriented the same, and densely packed (this causes the higher mean grey-value of the area), the dark spaces between the speckles have the same characteristics with regard to the shape.

In order to describe the working of the filter we introduce the following parameters: $\Lambda,\ \Gamma_B,\ \Gamma_T,\ M$, which represent the threshold mean grey-value above which an area is ill, the lower contrast beneath which an area is possibly healthy, the upper contrast above which an area is certainly ill, and the maximum number of iterations. As stated in section 2, we found experimentally that the following values are optimal: $\Lambda = 67,\ \Gamma_B = 30,\ \Gamma_T = 35,\ M = 4$.

We filter the region r in the following way:

- if $\mu_r > \Lambda$ or $\gamma_r \geq \Gamma_T$, (the area is certainly ill) then we apply the lighting procedure M times.
- if $\mu_r \leq \Lambda$ and $\gamma_r \leq \Gamma_B$, (the area is certainly healthy) then we apply the darkening procedure 4 times.
- if $\mu_r \leq \Lambda$ and $\Gamma_B < \gamma_r < \Gamma_T$, (it cannot be decided whether this is a healthy or an ill area), then we apply the darkening procedure $M\lfloor\frac{(\Gamma_T-\gamma_r)}{\Gamma_T-\Gamma_B}\rfloor$ times.

After this we pick the first next pixel outside r, grow a region s, we determine the texture parameters and we process s the same way.

The lighting and darkening procedures consist of simple spatial rules. For each pixel in the region we consider the eight neighbouring pixels. (See figure 2 for notation). Consider the following pairs:

$$R_0 = \{X_0, X_8\}, R_1 = \{X_1, X_7\}, R_2 = \{X_2, X_6\}.$$

(X_4 is the pixel under consideration).

x0	x1	x2
x3	x4	x5
x6	x7	x8

Fig. 2. The neighbourhood mask

The lighting procedure works as follows: For $i = 0, 1$ and 2 respectively: Compare the grey-value of X_4 with $\min(R_i)$. If $\min(R_i) > X_4$, then increase X_4 by 1. The darkening procedure is similar.

Note that no comparison of X_4 with the pair $\{X_3, X_5\}$ is made, for the following reason: Speckle is visible in medical ultrasound images as short thin white lines perpendicular to the sound beam. The reason for this is the properties of the sound beam together with those of the imaging system: because the sound beam diverges after its point of focus, the feasible "lateral resolution" decreases at greater depth. Furthermore the imaging system performs interpolation of the reflected signals to "fill up" the image and the speckles are "spread out" [13]. Since the whole scan is a 90 degrees sector the majority of speckles is horizontally oriented. so no correction in this direction is made.

4. EXPERIMENTAL RESULTS

In the figures 4-7 the results of the filter and the performance of the active contour are shown. Since the shapes in medical images are usually quite craggy, we choose the so-called GVF-snake, as presented in [5] and [6]. We used the programme that is delivered with the articles by the authors themselves, and set dmax (maximum distance between 2 active contour pixels) =2, and dmin (minimum distance between two active contour pixels) =0.5. As an edge detector we used the Canny detector with parameter $\sigma = 2.0$.

Figure 3 shows the original image as it is produced by the ultrasound scanner. One of the affected areas is delineated manually by an expert. We tried to segment the same area with the use of a GVF-snake starting from the initial position shown in figure 4. The final position we found is shown in figure 5. In figure 6 we show the filtered image. First we notice that visually the affected areas are more distinguishable now. Furthermore, when we apply the procedure with the active contour starting from the same initial position (figure 4), we find the result of figure 7.

5. CONCLUSION

In this paper we introduced a speckle suppression technique for medical ultrasound images that takes into account the

Fig. 3. Manual delineation of expert.

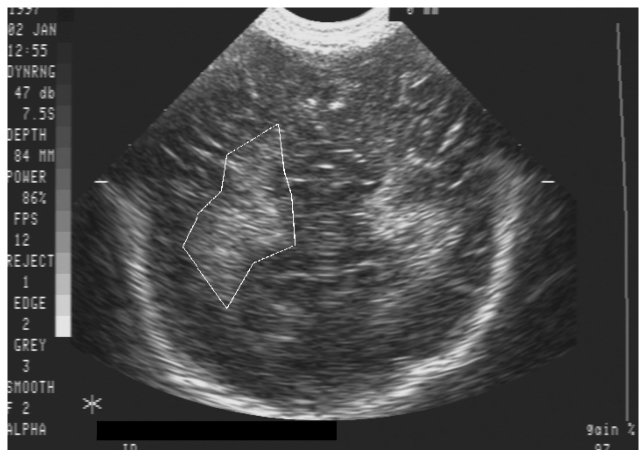

Fig. 4. Initial active contour position.

local medically based statistics of the image. On the resulting image a segmentation of the affected areas is performed by means of a GVF-snake, the result of which is compared with the manual segmentation performed by an expert. Our conclusion is that on the image processed by the proposed method, the GVF-snake performs considerably better with regard to finding the shape of the region of interest as well as with regard to finding the correct area, than on the unprocessed image. Finally, the proposed technique works fast and is not computationally intensive.

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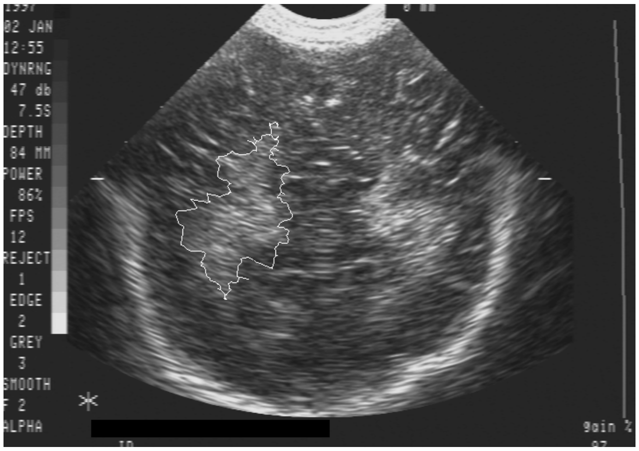

Fig. 5. Final active contour position

Fig. 6. Filtered image.

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Fig. 7. Final position in filtered image copied on original

vector flow," *IEEE Transactions on Image Processing*, vol. 7, no. 3, pp. 359–369, Mar. 1998.

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