Maximum Likelihood Signal Adaptive Filtering of Speckle In Ultrasound B-Mode Images

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Abstract - New techniques are presented for the processing of Ultrasound (US) B-mode images. A signal-adaptive Maximum Likelihood estimation algorithm is proposed, with local image adaptation based on a moving window. The algorithms are tested on US B-mode images obtained from simulated (phantom) and real liver scans[1].

I. Introduction

A number of methods [1-7] have been proposed in recent literature for the enhancement of Ultrasound Images. Linear noise elimination methods (such as spatial averaging) have been used, especially in early Ultrasound equipment. However, their use is limited because of their propensity to degrade the image through suppression of important edge and image detail information. Nonlinear techniques have offered a successful alternative to linear mothods.

Several Nonlinear techniques for speckle noise removal have been recently used. The suppression of speckle by an adaptive weighted median filter was proposed in [3]. The signal-adaptive median (SAM) filter proposed in [9] has also been applied for this purpose [5]. A novel adaptive nonlinear algorithm is developed and tested in the present work to suppress speckle while preserving local features such as edges. The basic global estimator is a Maximum Likelihood estimate based on the assumption of constant object signal intensity. Local adaptation is then based on measurements over a moving window. The algorithm is tested on simulated as well as real B-mode scans.

II. Maximum Likelihood Estimation

In general [2], the Ultrasound observation x is related to the underlying signal s by a relationship of the form $x = s + s^a n_1 + n_2$ where n_1 and n_2 are noise terms. In [6] it is assumed that the above noise model simplifies to

$$x = sn \tag{1}$$

where the noise n is Rayleigh distributed. This assumption is accurate prior to the nonlinear compression usually present in Ultrasound equipment. Based on (1) the folowing Maximum Likelihood estimator is developed [6]:

$$\hat{s}_o = \frac{\sqrt{\pi}}{2}\left(\frac{1}{N}\sum_{i=1}^{N} x_i^2\right)^{1/2} \tag{2}$$

Here, we shall use the model

$$x = s + s^a n \tag{3}$$

where n is a zero-mean Gaussian process independent of s. As is known, (3) approximates well the ultrasound observation-to-signal relation when log compression is on [3,4]. Typically, an appropriate value of a is considered to be $a = 1/2$ [3,4,9]. From (3) the following conditional density is easily calculated [10]

$$f_{x_i|s}(x_i \mid s) = \frac{1}{\sqrt{2\pi}\sigma \mid s^a \mid} \exp\{-(\frac{x_i - s}{s^a})^2/2\sigma^2\} \tag{4}$$

Thus, if $x_i, i = 1, \ldots, N$ are measurements of x in a window W around the pixel whose value s is to be estimated, the joint conditional density of the measurements is given by

$$f_{x_1,\ldots,x_n|s}(x_1, \ldots, x_n \mid s) = \prod_{i=1}^{n} f_{x_i|s}(x_i \mid s)$$

and is easily seen to be maximized at $\hat{s}_{ML}$, where $\hat{s}_{ML}$ is given by

$$\hat{s}_{ML} = -\sigma^2/2 + \sqrt{\sigma^4/4 + \hat{s}_o^2.4/\pi} \tag{5}$$

and a was assumed equal to 1/2. Equation (5) relates the maximum likelihood estimates of (4) before (s_o) and after (s_{ML}) compression. This is in rough agreement with the results in [7].

III. Local Adaptation

Local adaptation of the global Maximum Likelihood algorithm (5) will be effected by

$$\hat{s} = \hat{s}_{ML} + b[x - \hat{s}_{ML}] \tag{6}$$

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each pixel, where x is the observation and $\hat{s}_{ML}$ the Maximum Likelihood global estimate. The factor b will vary between 0 and 1. If b at some pixel approaches 1, the actual observation is retained; if b approaches zero, maximum noise reduction is achieved. In order to locally evaluate b, we define the local expectation operator

$$E_w\{x\} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{7}$$

where $x_i, i = 1, \ldots, N$ are the observations included in a window W about each pixel. The local mean-square error may now be defined by

$$e = E_w\{[s - \hat{s}]^2\}. \tag{8}$$

and the factor b in (6) may be selected so as to minimize e. As in [9], on differentiating (8) with respect to b and setting the derivative to zero, we find

$$b = \frac{E_w\{(x - \hat{s}_{ML})^2\} - E_w\{x\}\sigma^2}{E_w(x - \hat{s}_{ML})^2} \tag{9}$$

where W was assumed large enough so that the local averages approximate statistical means, $\hat{s}_{ML}$ is given by (5) $E_w\{x\}$ given by (7) and, explicitly,

$$E_w\{(x - \hat{s}_{ML})^2\} = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{s}_{ML})^2 \tag{10}$$

The final algorithm consists of (5) (6) and (9)

IV. Results And Conclusions

The algorithm was applied for speckle suppression and image segmentation purposes to both simulated images and real US B-mode images of the liver. Figure 1a shows a simulation of a homogeneous piece of tissue with a lession in the middle. The background differs from the lession in reflection strength. Figure 1b shows the result of the filtering performed by the signal adaptive maximum likelihood (SAML) filter described in this work. The lesion/background amplitude was improved from $5.22dB$ to $6.390dB$.

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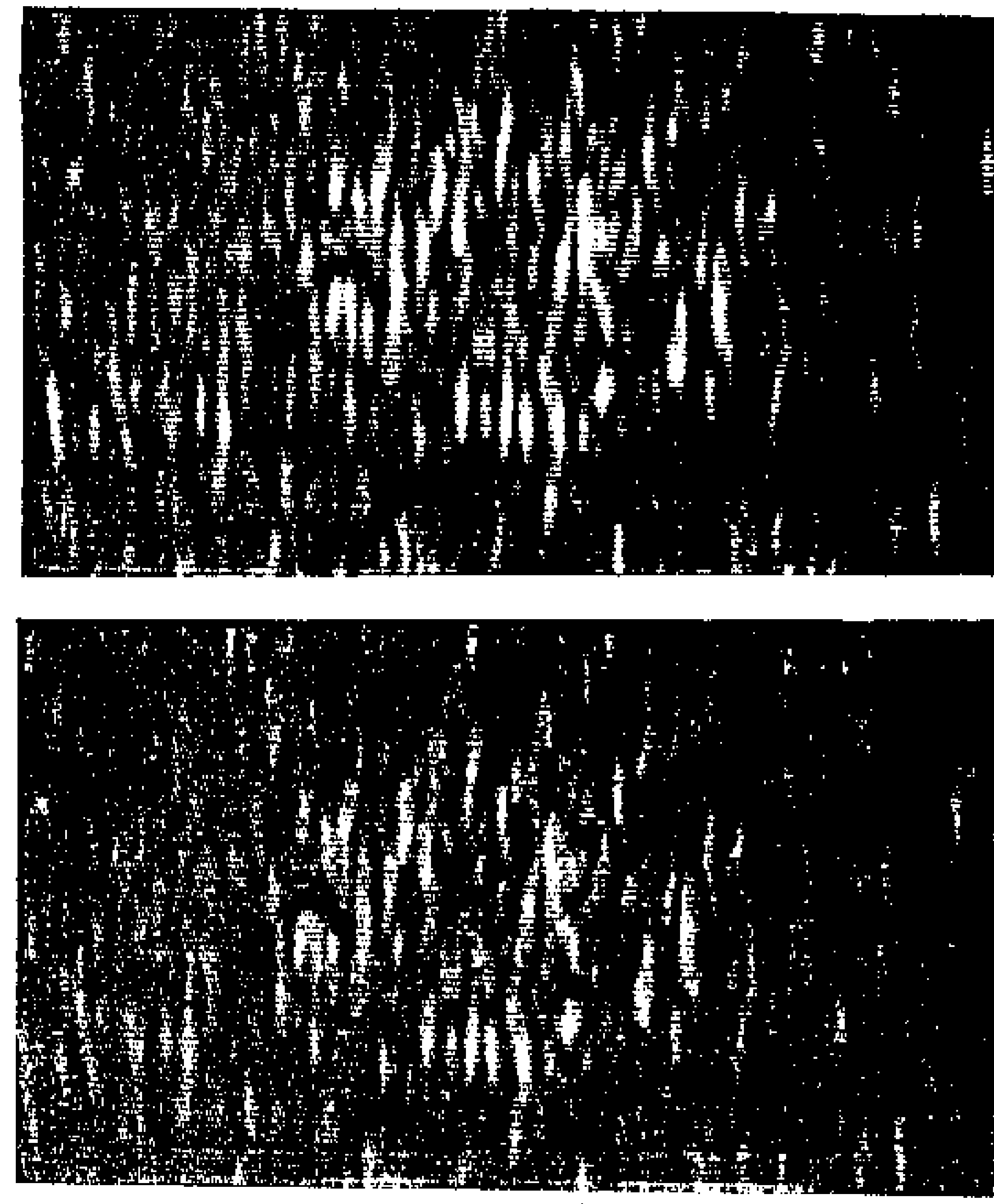

Figure 1: a. Original image, b. Result of filtering performed by SAML

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