ARCHIVES OF ACOUSTICS
23, 1, 115–124 (1998)

ADAPTIVE HYBRID METHODS FOR IMPROVING THE QUALITY OF ULTRASONIC IMAGES OF SKIN

M. LEWANDOWSKI, A. NOWICKI

Department of Ultrasound,
Institute of Fundamental Technological Research,
Polish Academy of Sciences
(00-049 Warszawa, ul. Świętokrzyska 21)

This study is concerned with methods for improving the quality of micro-ultrasonographic images using digital signal processing. A method of linear adaptive filtering is presented, which makes it possible to reduce speckle in ultrasonographic images, and its non-linear modification is proposed. Quantitative results of one-dimensional simulation of these filters is proposed and the results for real micro-ultrasonographic images of skin are presented.

1. Introduction

Crawford *et al.* [1] and Bamber *et al.* [2] presented the application of the LLMMSE (Local Linear Minimum Square Error) filter for improving the quality of two-dimensional ultrasonographic images. The presented algorithm belongs to a group of adaptive methods for reducing speckle in ultrasonographic images and is an alternative to the widespread methods for averaging a line in an image or whole images. The idea of the method lies in adaptive control of the degree of smoothing, depending on the local statistical properties of the image. The need for adapting the filter to local properties of the image results directly from the assumption that the signal is nonstationary. The local statistics of the image provide information about the similarity of a given area to speckle noise and, thereby, it determines whether this area should be smoothed with a low-pass filter or left intact. The operation of the filter described depends on two parameters, characteristic for the type of tissue under study. These are the gray level variance for areas with speckle characteristics and for those that contain biological structures. These parameters are able to distinguish between (classifies) speckle areas and biological structures.

Bleck *et al.* [3] studied the variability of the parameter in question which classifies speckle areas, depending on the measuring conditions and for different pathological changes in the kidneys under examination. These studies confirmed the usefulness of the adaptive speckle reduction method, also in the case of pathological changes causing the emerging of structural inhomogeneities (quasiperiodic structures) in tissue.

The subjective physicians' perception of ultrasonographic images filtered using the adaptive LLMMSE method was also studied. CRAWFORD *et al.* [4] demonstrated that almost in every other case the structural information in the images filtered was evaluated as better than in the original images. Better legibility of images processed in this way, without at the same time losing anatomical details, was also confirmed.

2. The filtering methods applied

This section presents the filter algorithms applied for improving the quality of micro-ultrasonographic images.

The quality of proposed filter methods was determined by simulation of one-dimensional signals. These methods were also integrated within the software of the micro-ultrasonographic device, permitting their usefulness to be checked in real clinical conditions.

2.1. LLMMSE type adaptive filtering

The original scheme of the LLMMSE method applied for speckle reduction in ultrasonographic images proceeds as follows:

• The input image is scanned by a filter window. Square windows with the dimensions 3×3, 5×5 and 9×9 pixels are most often used. Figure 1 shows the scheme of scanning an image with a square window with the dimensions 3×3 pixels. It can be seen in the figure that the central point does not reach the very edge of the image, causing the output image to be smaller than the original.

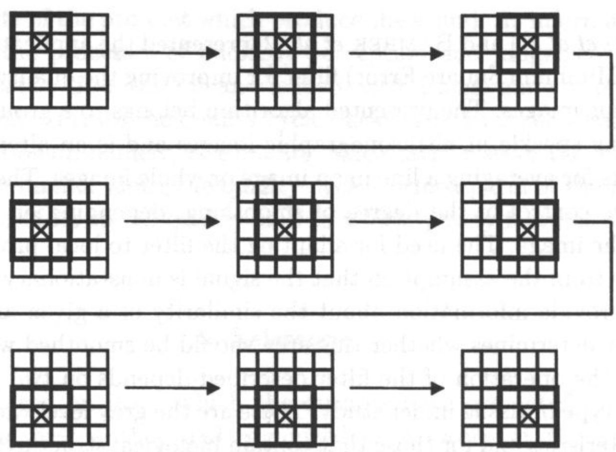


Fig. 1. An example of scanning an image with 5×5 points using a filter with the dimensions 3×3. (The central point of the window is marked with a cross).

• For every position of the window the local statistics are calculated (the grey level statistics of the pixels of the original image contained in the window): the mean $\langle x\rangle$ and the variance f. On the basis of these parameters and the parameters $f_{\text{structure}}$ and f_{speckle}

(determined arbitrarily – describing the statistical properties of the areas containing biological structures and speckle noise, respectively), the coefficient k is calculated:

$$k = \frac{(f - f_{\mathbf{speckle}})}{(f_{\mathbf{structure}} - f_{\mathbf{speckle}})}, \tag{1}$$

where f is the calculated value of the variance in the window.

It is then restricted to the interval $[0, 1]$, i.e., $k = 1$ when $k > 1$ and $k = 0$ when $k < 0$.

• Finally, the output value of the filter is calculated in the following way (Fig. 2):

$$x_{\text{out}} = \langle x \rangle + k \cdot (x_{\text{in}} - \langle x \rangle), \tag{2}$$

where x_{in} is the grey level of the input image which is at the central point of the filter window, $\langle x \rangle$ is the calculated mean grey level in the window and k is the calculated weight coefficient (cf. Eq. (1)).

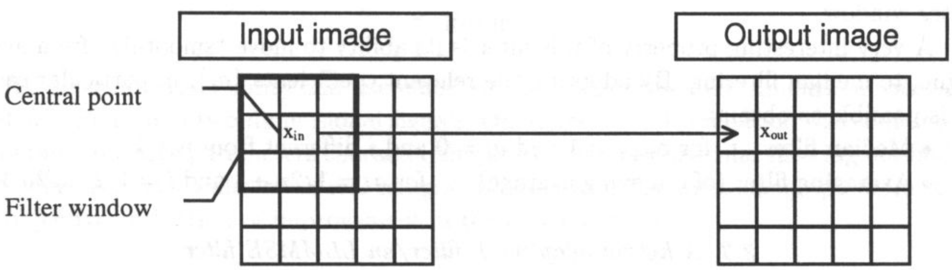


Fig. 2. The processing scheme for a single 3 × 3 window, (see Eq. (2)).

The parameters $f_{\text{structure}}$ and f_{speckle} are determined from analysis of the areas containing only biological structures and speckles, respectively, for a given type of tissue under examination. These coefficients are a criterion of similarity for the local properties of the image, and determine, through the coefficient k, the degree of smoothing of the local area BAMBER *et al.* [2].

The above algorithm makes use of the variance/mean ratio to identify the noise areas (speckle areas), and it is based on the assumption that a linear dependence is present between the variance and the mean. As was demonstrated by CRAWFORD *et al.* [1], the above assumption requires linear or logarithmic characteristics of the input circuit of the ultrasonograph. These authors examined the input characteristics of several universally used ultrasonographs and proposed methods for correcting those characteristics that did not satisfy the assumptions of LLMMSE filtering.

2.2. L-filters

L-filters can be considered a modification of a linear finite impulse response (FIR) filter. After windowing of the input data the proper ordering of samples is done and next FIR polynomial is constructed (Fig. 3).

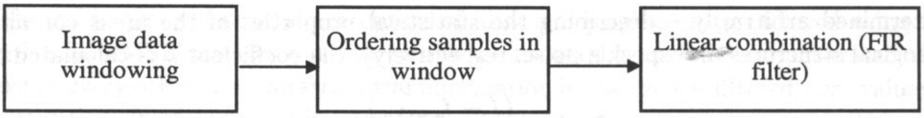


Fig. 3. A schematic representation of the working of an L-filter.

L-filters can be also considered as a generalisation of a median filter using all the signal samples instead of only the median. A basic advantage of filters of this type is their ability to cope with different types of noise.

The linear combination of FIR filtering is conducted on the ordered sequence $\{x_i\}$ of input signal samples.

$$y = \sum_{j=1}^{2n+1} a_j \cdot x_j \,, \tag{3}$$

where a_j are constant coefficients of the linear FIR filter and $2n+1$ is the length of the filter window.

A very interesting property of this filter is its ability to move "smoothly" from averaging to median filtering. By adopting the relevant coefficients $\{a_i\}$, in particular cases it is possible to obtain:

- Median filter for $a_{n+1} = 1$ and $a_i = 0$ and i different from $n+1$.
- Averaging filter (of a moving average) for $a_i = 1/2n+1$ and $i = 1, 2, ..., 2n+1$.

2.3. A hybrid adaptive L-filter/an LLMMSE filter

Since an LLMMSE type filter failed to cope with pulsed noise [5, 6], a hybrid filter was proposed, which combined the advantages of a linear and median filters. The LLMMSE algorithm was preceded by ordering signal samples (according to their values), just as was the case with L-filters. Such an approach permitted optimum filtering of nonstationary noise (a property of an LLMMSE filter) while maintaing edges within the image (a property of a median filter).

Schematically, the hybrid algorithm is as follows:

- The input image is scanned using the filter window – analogously to the case of the LLMMSE algorithm.
- In the second stage, the samples from the filter window are ordered according to the grey level of pixel. In the case of a classic median filter, a point in the output image would be the median from the sequence ordered in this way.
- For every window, the local statistics are calculated: the mean $\langle x \rangle$ and the variance f – as in the LLMMSE algorithm (sample ordering is insignificant for the parameters calculated in this step).
- Finally, the output value of the filter is calculated, just as for the LLMMSE filter, except that the mean value $\langle x \rangle$ as in formula (2) is replaced by the median x_{med} (calculated in the filter window)

$$x_{\text{out}} + k \cdot (x_{\text{in}} - x_{\text{med}}). \tag{4}$$

2.4. A modified hybrid filter

The hybrid filter presented in the previous section takes over the ability to keep details (the edge) from the median filter. It is known that most details preserved by the median filter depend on the size of the window. The process of ordering samples in the window can also be understood as a loss of information about the position of samples (in terms of time or space). In the case of ultrasonographic images in B-mode presentation, both time information (along the wave propagation axis) and space information (along the head movement direction) is lost.

The use of a weighted median is a method for preserving information about the position of samples. The weighted median filtering is obtained by a duplication of pixel values in the filter window before ordering them. As a result, it is possible to ensure a larger number of representative samples situated in the input window at a predetermined position (most frequently, the central one).

3. Results

To determine the quality and usefulness of the filters presented, simulation was carried out of one- and two-dimensional signals. One-dimensional simulation was conducted to obtain objective parameters characterizing the quality of particular filtering methods. Two-dimensional simulation of real images obtained from the ultrasonograph permitted an objective evaluation of improvement in the image quality.

3.1. One-dimensional simulation

To determine the properties of the filters presented, a simulation was performed for noise-perturbed one-dimensional signals. In the simulation, a section of a real ultrasonographic signal was used (Fig. 4). Noise with a Rayleigh distribution and pulsed noise were added to the input signal. The noise with a Rayleigh distribution in the signal of line A was a result of demodulation of a high-frequency ultrasonographic signal containing Gaussian noise. Pulsed noise was added to provide for simulation of the lack of signal or saturation occurring in the course of digital-to-analog conversion, resulting from the non-ideal nature of the clock synchronizing the processing.

The mean square signal-to-noise ratio $\mathrm{SNR_{MS}}$ was determined as a measure of signal improvement. The value of this parameter was expressed in dB, calculating

$$\mathrm{SNT_{MS}}(s,x) = 10 \cdot \mathrm{LOG}\left(\frac{\sum\limits_{i=1}^{N}(x_i)^2}{\sum\limits_{i=1}^{N}(s_i - x_i)^2}\right) \ [\mathrm{dB}], \tag{5}$$

where $\{s_i\}$ is the sequence of samples of the original signal, $\{x_i\}$ is the sequence of samples of the noise-perturbed signal before (after) filtering, and N is the length of the sequence of signal samples.

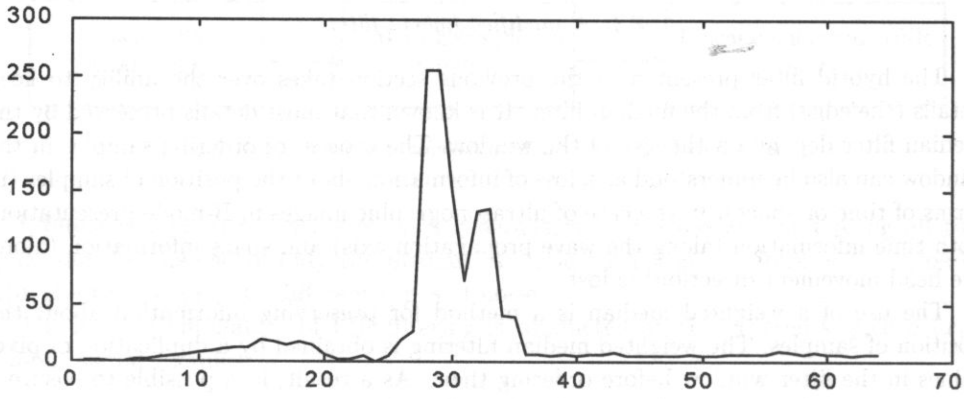


Fig. 4. A section of the signal of line A, used in one-dimensional simulation.

The parameter defined in this way was calculated for a noise-perturbed signal (i.e., before filtering) and then for the signal after filtering. An increase in the value of the ratio SNR_{MS} means signal improvement.

The results obtained for different values of the power (variance) of the added Rayleigh noise and different probabilities of pulsed noise always show the same tendency, i.e., a positive edge of the hybrid filter over the simple LLMMSE algorithm. The diagram below shows the simulation results for the variances of Rayleigh noise equal to 10, 20 and 30 and for the filter window with the length of 9. For all the results shown below, the probability of pulsed noise was 0.01.

Table 1. The results of one-dimensional simulation.

Values of the coefficient SNRMS in [dB]			
Input signal	Averaging filter	LLMMSE filter	Hybrid filter
12.86	3.15	13.84	15.54
8.03	3.41	9.63	10.99
5.77	3.43	7.27	8.17

Table 1 shows the values of the calculated coefficient SNR_{MS}, corresponding to the diagram in Fig. 5. The result of the work of the simplest averaging filter is also given as a reference. It can be seen that in this case the averaging filter very distinctly worsens the signal to noise ratio. This behaviour may be explained with two factors. Firstly, the added noise was Rayleigh rather than Gaussian noise; the averaging filter copes well with the latter. Secondly, the signal being filtered was a fast changing (high-frequency) one compared with the low cut-off frequency of the averaging filter (which was a low-pass filter) related to the length of the filter window. In the case of fast changing signals, the distortions caused by the averaging filter for an excessively long filter window may drastically worsen the signal to noise ratio.

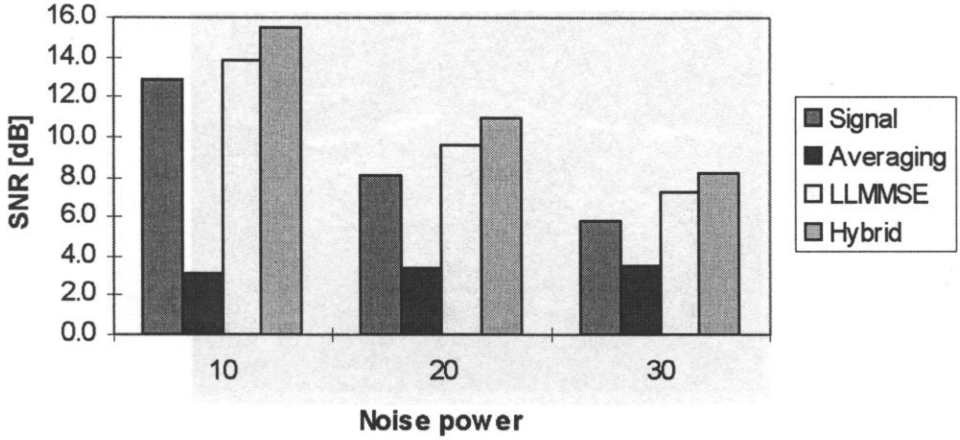


Fig. 5. The results of simulation for three different noise variances.

3.2. Two-dimensional simulation

The described filtering algorithms were applied to the series of skin images recorded from healthy volunteers and from patients with different skin melanoma e.g. superficial spreading melanoma, nodular melanoma or lentigo malignant melanoma.

The example cases are presented in the following way; the top picture is an original non-filtered image, middle one shows the same pattern after applying LLMMSE filtering and the bottom one shows the resulting image after hybrid filtering.

These photographs distinctly show the effect of the work of the filters. Both filters reduce the grain content in the image. The effect of the hybrid filter is more conspicuous, since it removes details with sizes smaller than the window length (classified as pulsed noise). The LLMMSE filtered image contains these small disturbances, therefore, it appears to be slightly sharper than the image following the hybrid filter. Both examples (Figs. 6 and 7) prove the positive impact of filters can be seen, permitting the boundaries of pathological change areas to be determined.

4. Conclusion

In micro-ultrasonographic images there are the same types of noise as in ultrasonographic ones. As an effect of this, the use of the adaptive method for speckle reduction, applied in conventional ultrasonography, brought a positive result in the case of micro-ultrasonographic images. The proposed nonlinear modification of LLMMSE filtering made it possible to improve further the signal-to-noise ratio. As the simulation on real skin and eye images indicated, both methods ensure subjective improvement in the quality of the images obtained.

a)

b)

c)

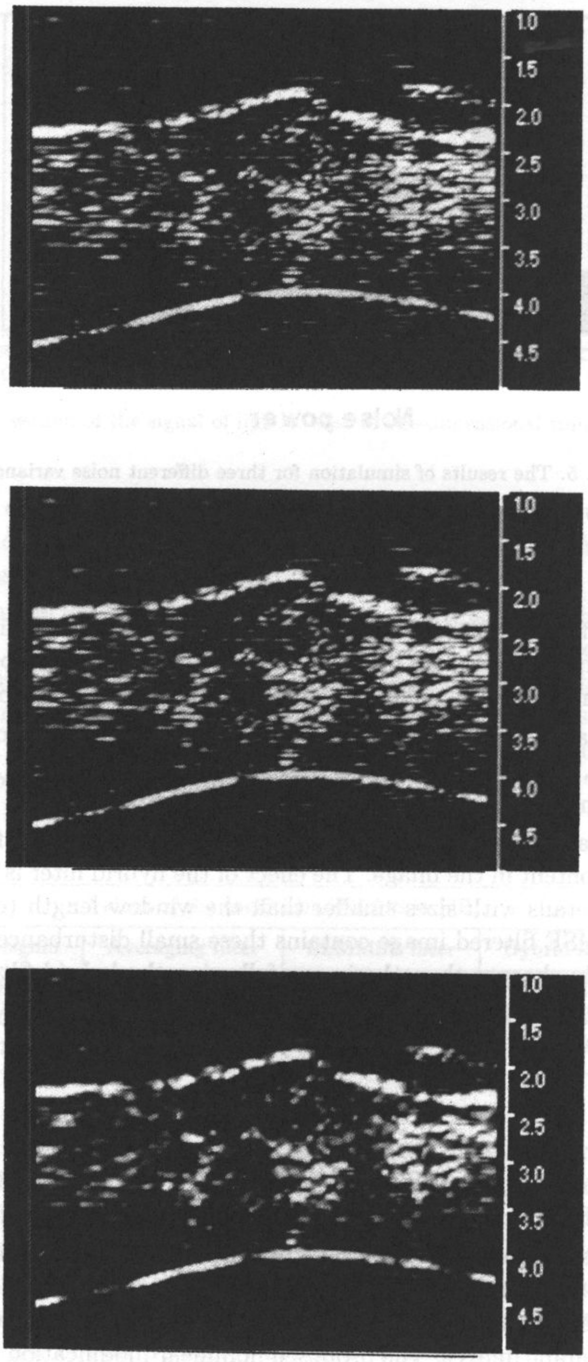
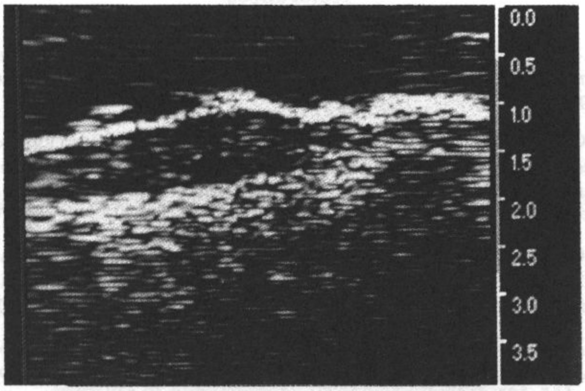
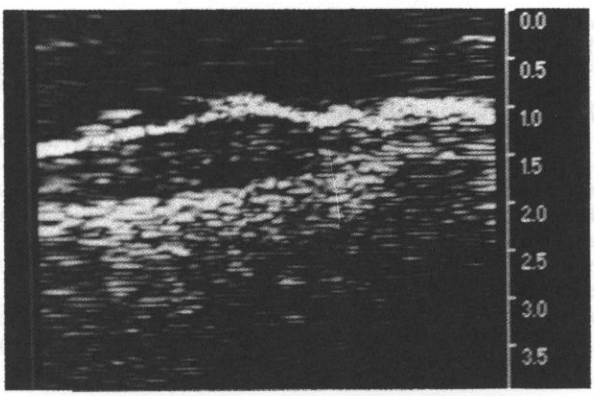


Fig. 6. Sector scan of superficial spreading melanoma, a) original image, b) after LLMMSE filtering, c) after hybrid filtering.

a)



b)



c)

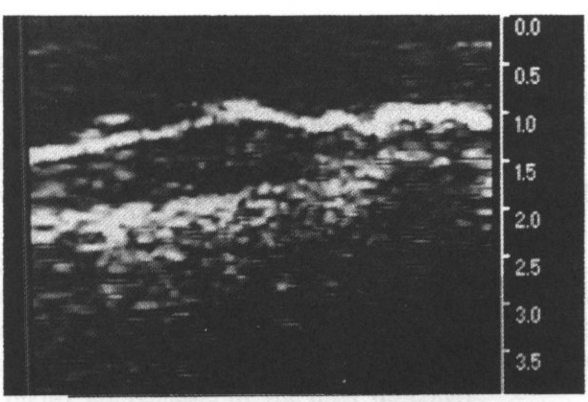


Fig. 7. Sector scan of nodular melanoma, a) original image, b) after LLMMSE filtering, c) after hybrid filtering.

References

[1] D.C. CRAWFORD, D.S. BELL, J.C. BAMBER, *Compensation for the signal processing characteristics of ultrasound B-mode Scanners in adaptive speckle reduction*, [in:] Ultrasound in Med. & Biol., Vol. 19, No. 6, 469–485, 1993.

[2] J.C. BAMBER, D.C. CRAWFORD, D.A. BELL, C.C. HARLAND, B.A. GUSTERSON, P.S. MORTIMER, *Effects of speckle reduction processing on ultrasound B-mode images of skin tumours*, [in:] Acoustical Imaging, H. ERMERT H., H. MARJES [Eds.], Plenum Press, New York & London, Vol. 19, 447–452, 1992.

[3] S.J. BLECK, M. GEBEL, M. HEBEL, S. WAGNER, K. SCHMIDT, S. KRUIP, M. WESTHOFF-BLECK, M. WOLF, C. THIESEMANN, M. MANNS, *Tissue characterization using intelligent adaptive filter in the diagnosis of diffuse and focal liver disease*, Ultrasound in Med. & Biol., **20**, 6, 521–528 (1994).

[4] D.C. CRAWFORD, D.O. COSGROVE, E. TOHNO, W.E. SVENSSON, B. AL-MURRANI, D.S. BELL, K. STEPNIEWSKA, J.F. BAMBER, *Visual impact of adaptive speckle reduction on US B-mode images*, Radiology, **183**, 2, 555–561 (1992).

[5] T. SUN, M. GABBOUJ, Y. NEUVO, *Adaptive L-filters with applications in signal and image processing*, Signal Processing, 38, 331–344 (1994).

[6] T.S. HUANG [Eed.], *Two-dimensional digital signal processing II*, Springer-Verlag, Berlin, Heidelberg, New York 1981.