Improved Adaptive Median Filter for Denoising Ultrasound Images

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Abstract: - This paper presents a fast and easy method to implement denoising of ultrasound images. One of the very important tasks in the field of image processing is the removal of noise from an image. Noise may arise in the process of image acquisition, its transmission and also in the reproduction of an image. There are several approaches regarding the task of denoising, depending on the nature of the noise. Some image restoration techniques are best formulated in the spatial domain, and in this paper propose improved algorithm and compare their effectiveness. On different test examples our method achieved very good results so it can be considered a promising tool for such corrections.

Key-words: - Image processing, Denoising algorithms, Medical images, Digital filters, Ultrasound images, Signal Processing

1 Introduction

Digital images are nowadays used almost everywhere and in most cases some image processing is required. In many applications it is of crucial importance since without it images would be useless. Examples are many medical images originated by alternative sources like ultra-sound or x-rays or images from cameras on remote locations where it is impossible to correct problems like damaged optics or undesirable movement on the spot. Digital images are acquired via some imaging apparatus or sensor, stored on a digital medium and are very likely transmitted across networks. At each of these steps noise can be acquired, though the principal sources of noise in digital images arise during image acquisition (digitalization) and/or transmission [1].

In this paper we will use three most common noise models to simulate image degradation (Gaussian, uniform and impulse noise) and also the various local algorithms, including an example of an adaptive algorithm, that tackle the process of denoising an image.

We propose a method of designing improved adaptive image processing filters. The research described in this paper focuses on the application of digital filters in the spatial domain to reduce speckle noise in ultrasound images.

This research is supported by Ministry of Science, Republic of Serbia, Project No. 44006

2 Related work

The field of denoising is still very active today, with research involving many local and non-local algorithms (in terms of the processed images), working on both spatial and frequency domains. There are also machine learning algorithms that are effectively used in this process. Image denoising still remains a challenge for researchers because noise removal introduces artefacts and causes blurring of the images [2].

The applications of imaging denoising are many. For instance, many algorithms developed for tasks in computer vision, such as object recognition, segmentation and others, assume that the input images contain little or no noise [3]. In medicine for example, the fundamental problem of ultrasound images is the poor quality, mainly caused by multi-scale speckle noise [4].

Image denoising has been extensively studied and many approaches have been investigated for the process of noise removal. In the article [7] we have comparative evaluation of five commonly used image enhancement techniques, each with a different fundamental theory behind it, applied on the domain of ultrasound images - spatial and frequency domain filtering, histogram processing, morphological and wavelet filtering. Quality measures for this analysis are useful to us in deciding how to quantify the effect and possible improvements of algorithms that we implement.

Since one of the characteristics of ultrasound images is speckle noise, the article [13] deals thoroughly with filters that specifically target

ISBN: 978-1-61804-126-5

speckle noise and use quality measures which are well suited for this kind of an investigation.

Another highly relevant work is [14] which incorporates dynamical computing of image statistics, based on which the non-linear, non-local algorithm changes its behaviour. The method described manages to avoid the degrading or removal of fine detail and texture of an image, which happens in many other previously studied algorithms.

Also, there are many papers which are based on wavelet manipulation, such as [4], [5] and [9]. The methods described in these papers warrant the improvement of the subjective image quality without providing any noticeable artefacts.

3 Ultrasound image denoising

Ultrasound imaging is inexpensive, widely available and safe to the users as well as the operators. For these reasons, it is one of the most preferred imaging techniques in medicine [7]. However, medical images often consist of low-contrast object corrupted by random noise arising in the image acquisition process.

Noise removal has been extensively studied and many denoising methods have been proposed. In medical imaging, denoising is challenging since all kinds of noise cannot be easily modelled and depend on the tissue being imaged. This is the case with ultrasound images, where we encounter speckle noise which obscures fine details and has an adverse effect in the detection of low-contrast lesions. In the imaging process, the energy of the high-frequency waves is partially reflected and transmitted at the boundaries between tissues having different acoustic impedances [6].

Due to the presence of speckles in ultrasound images, enhancement is extremely difficult, especially in images of liver and kidney whose underlying structures are too small to be resolved by large wavelength [8]. Thus, where retention of the subtle structures of the image is important, the performance of noise suppression must be balanced with the filter’s effectiveness in order to preserve fine detail [10].

Image noise is random variation of brightness or colour information in images. It is an undesirable by-product of image capture that adds spurious and extraneous information.

The noise embedded in an image manifests in diverse varieties. The noise may be correlated or uncorrelated; it may be signal dependent or independent, and so on. The knowledge about the imaging system and the visual perception of the image helps in generating the noise model. Estimating the statistical characteristics of noise embedded in an image is important because it helps in separating the noise from the useful image signal.

We can represent a noise degraded image in the spatial domain with the following equation:

$$g(x,y) = h(x,y) * f(x,y) + \eta(x,y) \tag{1}$$

where h(x,y) is the spatial representation of the degradation function, η(x,y) is an additive noise term and the ‘*’ symbol indicates convolution. Since convolution in the spatial domain is equal to multiplication in the frequency domain, we may write the model in an equivalent frequency domain representation:

$$G(u,v) = H(u,v)F(u,v) + N(u,v) \tag{2}$$

where the terms in capital letters are the Fourier transforms of the corresponding terms in the previous equation for the spatial domain.

In this paper we will be only concerned with case when *H* is an identity operator and will be dealing solely with degradations caused by noise.

We assume that noise is independent of spatial coordinates and that there is no correlation between pixel value of the image and the value of noise components. We will also be concerned with the spatial noise descriptor, i.e. the statistical behaviour of the gray-level values in the noise component of the model, as characterized by a probability density function (PDF) or random variables. We will deal with Gaussian noise, Uniform noise, Impulse noise (salt-and-peper)

4 Spatial Denoising algorithms

Various factors are involved in the generation of noise in the image acquisition process, including environmental factors and the properties of the sensing elements used. During transmission, noise can occur due to interference in the transmission channel.

We assume that noise is independent of spatial coordinates and that there is no correlation between pixel value of the image and the value of noise components. We will also be concerned with the spatial noise descriptor, i.e. the statistical behaviour of the gray-level values in the noise component of the model, as characterized by a probability density function (PDF) or random variables. Often, it is possible to use small areas of the image, with a constant gray level, to estimate the parameters of the PDF. By analyzing the histogram shapes of these regions, we may

ISBN: 978-1-61804-126-5

identify the closest PDF match. We use the mean and variance for estimating the parameters of Gaussian and uniform noise models. Impulse noise parameters are estimated by selecting a small patch of the image, of constant mid-grey colour, and retrieving the probability of occurrence of black and white pixels.

Spatial filtering is the method of choice in situations when only additive noise is present [1].

Arithmetic mean filter. The simplest of mean filters, the arithmetic mean filtering process computes the average value of the corrupted image g(x,y) in the area defined by S_xy (a rectangular subimage window of size m×n, centred at the point (x,y).

$$\hat{f}(x,y) = \frac{1}{mn} \sum_{(x,y)\in S_{xy}} g(x,y) \tag{8}$$

Noise is reduced as a result of blurring.

Geometric mean filter. The geometric mean filter uses the geometrical mean as a basis of blurring, to a similar effect of the arithmetic mean filter, but with a tendency to lose less image detail in the process.

$$\hat{f}(x,y) = \left[\prod_{(x,y)\in S_{xy}} g(x,y)\right]^{\frac{1}{mn}} \tag{9}$$

Harmonic mean filter. The harmonic mean filter works well for salt (and other, like Gaussian) noise, but fails for pepper noise. It is defined by the expression:

$$\hat{f}(x,y) = \frac{mn}{\sum_{(x,y)\in S_{xy}} \frac{1}{g(x,y)}} \tag{10}$$

Contraharmonic mean filters. Where Q is the order of the filter, the contraharmonic filter is defined by the expression:

$$\hat{f}(x,y) = \frac{\sum_{(x,y)\in S_{xy}} g(x,y)^{Q+1}}{\sum_{(x,y)\in S_{xy}} g(x,y)^{Q}} \tag{11}$$

It is well suited for eliminating salt noise (when Q is negative) or pepper noise (when Q is positive). Harmonic and a negative Q contraharmonic filter both work well with salt noise. For pepper noise, we find that only a positive Q contraharmonic filter worked well.

Median filter. This is the best-known order-statistics filter, which replaces the value of a pixel by the median of the grey levels in the neighbourhood of that pixel.

For certain types of noise, these filters provide excellent noise-reduction, and are particularly good at dealing with both unipolar and bipolar impulse noise.

The median filter was successful in dealing with both salt and pepper noise.

Max and min filters. These are also order-statistics filter, useful at identifying the brightest and the darkest points of an image, by replacing a pixel's value by the maximum (or minimum) value in its neighbourhood. Max filter can help reduce pepper noise, while min filter reduces salt noise.

The max and min filters were successful in removing the corresponding noises, with a noticeable loss of quality and details of the image.

Midpoint filter. A combination of the max and min filters, the midpoint filters work best for randomly distributed noise, such as Gaussian or uniform noise.

5 Adaptive filters

An adaptive filter's behavior changes based on statistical characteristics of the image inside the filter region, as defined by the mxn region S_xy. These filters are of a greater complexity and analyse how image characteristics vary from one point to another.

The adaptive median filter preserves detail while smoothing impulse noise. It changes the size of the working window S_xy during execution, according to specified conditions. First, we define the following:

$$\begin{aligned}
z_{min} &= \text{minimum grey level value in region } S_{xy} \\
z_{max} &= \text{maximum grey level value in region } S_{xy} \\
z_{med} &= \text{median of grey levels in region } S_{xy} \\
z_{xy} &= \text{grey level at coordinates } (x,y) \\
S_{max} &= \text{maximum allowed size of } S_{xy}
\end{aligned} \tag{12}$$

The adaptive median filtering algorithm can be represented with the following pseudo-code:

```
if z_min < z_med < z_max:
    if z_min < z_xy < z_max:
        return z_xy
    else:
```

ISBN: 978-1-61804-126-5

```
        return z_med
else:
    increase window_size
    if window_size <= S_max:
        continue
    else:
        return z_xy
```

The values of z_min and z_max are considered by the algorithm to be impulse-like noise components. If the median of the working region falls between these two values, then we do not consider it an impulse. If so, then we check whether the point in the centre of the region is itself an impulse, by seeing whether z_xy is between the minimum and maximum value. If this condition holds, then the algorithm returns the original value of the pixel. If not, then the value of the pixel is extreme and the algorithm outputs the median value.

If we had previous found an impulse (for the median of the working region), we increase the size of the window and restart the algorithm from the beginning.

For smaller noise probabilities or larger maximum working region size S_max, it is less likely that we will exit the algorithm prematurely. The choice of the maximum value can be estimated by experiment with the “standard” median filter first.

Every time the algorithm returns a value, the window is moved to the next location in the image and the algorithm is reinitialized, working with the pixels in the new location.

6 Improved adaptive median filter

The problem with the previously described filter is that it does not work well with Gaussian and speckle noise. Since these are the very kinds of noise one encounters in ultrasound image, we constructed a modified algorithm, which uses the Euclidean distance as a measure of “smoothness” of the working window, which is compared to a cutoff value, with which we fine-tune the algorithm to detect noise.

We defined the following additional variables:

$$z_{avg} = \text{mean grey level value in region } S_{xy}$$

$$euc_{avg} = \text{average Euclid distance in region } S_{xy}$$

$$cutoff = \text{limit for the Euclidean distances in } S_{xy}$$

The algorithm is described with the following pseudo-code:

```
calculate z_avg for the working window
calculate Euclidean distances between z_avg and all other pixels in the working window
calculate average Euclidean distance for this working window as euc_avg
if euc_avg > cutoff:
    return z_med
else:
    increase window_size
    if window_size <= S_max:
        continue
    else:
        return z_xy
```

The algorithm works block-wise and considers pixel data which deviates from a pre-set norm to be originating from a noise signal. In this case, the value of the central pixel for the working window is replaced by the median intensity value of the working window, since median filtering with local statistics is found to be effective in handling grainy-patterned speckle noise [11]. Figures 1 and 2 show the effectivness of this method.

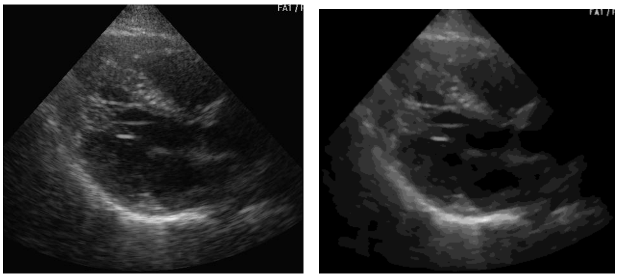

Figure 1. Example ultrasound image of the heart (left) and with modified algorithm, cut-off 10

The software that has been developed alongside this paper allows experiments with images and provides implementation of the various algorithms there mentioned. The application was developed in the C# language, as the language is easy to understand and provides fast prototyping and development speeds.

The image data is handled with custom functions and classes that operate on the low-level (as it would be done in a language such as C for instance), without the use of high-level libraries that are available, to better illustrate the algorithms that are implemented and to provide better portability and higher speed.

Among the software features are some basic image manipulation functions, adding of different types of noise to an image and of course, the implementations of different denoising algorithms. There are also some example images included, on which the various experiments were undertaken in

ISBN: 978-1-61804-126-5

this paper, that were publicly available from the Digital Image Processing website: www.prenhall.com/gonzalezwoods and from Wikipedia, available under the creative commons licence (Unequalized Hawkes Bay NZ.jpg by Phillip Capper).

7 Experiments

In this section the results achieved by using the proposed method with our software are presented.

The advantage of using our proposed method is the success in removing speckle noise associated with ultrasound images while preserving the fine details associated with observed tissue, such as kidney tissue.

We used images from the Samsung Medison Ultrasound Image gallery (www.medison.ru/uzi) as our test data.

As our measures of quality, we relied on both objective and subjective evaluations. The objective measures were Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSTN) and Speckle Suppression Index (SSI). The SSI tends to be less than 1 if the filter performance is efficient in reducing the speckle noise [12].

First, we experimented with adjusting the cut-off value for the average Euclidean distance measure and the maximum window size for our developing algorithm. As can be seen in Table 1 and Figure 3 the results suggest that the best cut-off value for images of this particular domain seem to be in the range [10, 15], depending on the image in question.

Cut-off	MSE	PSNR (db)	SSI
5	948.2102	18.3618	0.9221
10	953.2195	18.3389	0.9192
15	988.0245	18.1831	0.9069
20	1064.8310	17.8580	0.8978
30	1147.7163	17.5325	0.9162

Table 1 Quality measures for different cut-off values of the modified adaptive median filter

Cut-off values above 30 produced results that were so blurry that they were unusable for any practical use for a medical expert.

The numerical results suggest that the best cut-off rate is also the lowest one. As this value is lower, this has as a result of reducing this algorithm to the standard median algorithm. Also, this does not match the visual reduction in speckle noise that can be seen for slightly higher values.

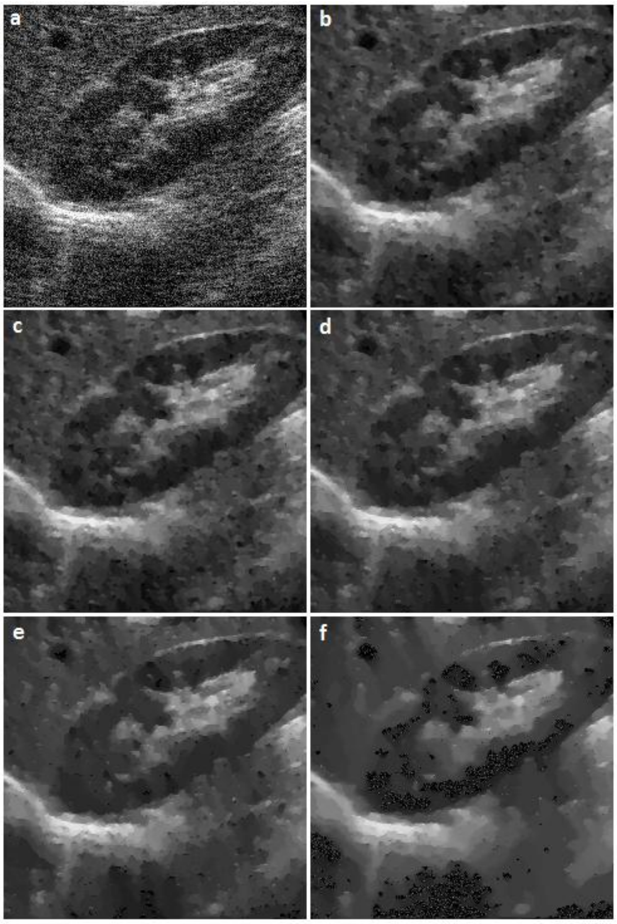

Figure 3. Visual results of the new adaptive filter, for different Euclidian distance cut-off values: (a) original image, (b) cutoff = 5, (c) cutoff = 10, (d) cutoff = 15, (e) cutoff = 20, (f) cutoff = 30

Next we applied the median and adaptive median filters for comparison. The results in table 2 suggest that both the adaptive median filter was a step in the right direction, except that the noise was still largely present.

Filter	MSE	PSNR (db)	SSI
Median	72.2283	29.5437	0.9872
Adaptive	39.5659	32.1576	0.9827
Modified	153.8730	26.2592	0.9695

Table 2 Comparative quality measures for the median, adaptive and modified adaptive filters.

What the data shows is that the modified algorithm fares poorly in comparison with the median and adaptive median filters. However, these measures do not take into account the subjective impression of success in reducing the speckle noise, which can be seen in the visual results. This is equally important, as these images would later be available for use by medical personnel, who must be able to easily and correctly identify various hallmarks and features on the images.

ISBN: 978-1-61804-126-5

There is certainly room for improvement of the modified adaptive median algorithm, one of which could be to use a finer measure than the Euclidean distance, to better differentiate between noise signals and genuine features and edges in an images.

8 Conclusion

In this paper, we worked with the assumption that image degradation can be modelled as a linear, position-invariant process with the addition of (additive) noise that is not correlated with image values. We can obtain useful results by simulating various types of additive noise and applying the various filters (working on the spatial domain) that were provided in the previous sections.

We developed a method which takes into account statistical characteristics of noise-like signal and utilises the effectiveness of iterative, adaptive methods. It could also be used as a template for more effective methods that would operate on the spatial domain, by modifying the test condition for noise-detection and the denoising itself.

Each filter works best for certain types of noise and performs not so well on others. An observer's preferences and capabilities must be taken into account, as well as the function in which the images are utilised (such as ultrasound imaging) since the denoising process has to rely on subjective interpretations of an individual image's "enhancement" or "restoration". Therefore, the area of denoising remains a challenge for further improvements in the field.

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