ON IMPROVING THE NOISE REDUCTION ALGORITHMS USING IMAGE SEGMENTATION

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ABSTRACT

This paper discusses how a partial segmentation of an image can be used to enhance the performance of existing wavelet noise reduction algorithms. It demonstrates that the spatial decomposition, provided by the segmentation, complements the frequency based decomposition of the wavelet transform, leading to better localisation of objects and allowing improvement of the noise reduction schemes.

1. BACKGROUND

Image noise reduction is a low-level tool utilised in a variety of ways within range of image processing tasks, on of the most obvious examples being the enhancement of images for archiving purposes. A great many noise reduction schemes have been proposed. One of the most popular and powerful classes of methods is based on wavelet decompositions [1-6]. These methods are based on first decomposing the image into its wavelet components, the second stage is to apply a non-linear function (an operation variously called shrinkage, thresholding or coring), with the final image being reconstructed by applying the inverse wavelet transform to the modified coefficients. The manifold variants of this scheme arise from making different choices for the form of wavelet transform used, different thresholding schemes employed and differing techniques to adapt the parameters of the thresholding schemes to a particular image.

Both decimated and undecimated wavelet decompositions can be used for noise reduction. The decimated forms, whilst be computationally efficient, do tend to produce lower levels of noise reduction and can cause perceptible blocking artefacts in the final image. For these reasons the undecimated wavelet transforms have found increasing favour in recent years and it is algorithms based on such decomposition that will form the basis of the work presented herein.

An important element of any image noise reduction scheme is how one relates the measurable properties of a noisy image to the parameters of the thresholding scheme. Typically some estimate of the variance of the contaminating noise is obtained, through one of a variety of measures [2,4-6], this noise variance can then be combined with the variance of the noisy image to get an estimate of the signal to noise ratio (SNR) for each wavelet component. Generally components with high SNRs have a gentle thresholding function applied, whilst low SNR components are thresholded in a more aggressive manner. A seminal paper describing an efficient and effective method for achieving this is [5].

The key to the use of image segmentation is the observation that natural images are not homogeneous (in space). The implication of this is that the SNR varies as a function of location on the image. This implies, from the above discussion, that the parameters of the thresholding scheme should vary as a function of location and it is just such a scheme that forms the basis of this paper. By first segmenting the image into local regions, we are able to estimate the SNR with each region, for each wavelet coefficient, and so apply a thresholding function that is adapted to the location and frequency (scale) of a pixel.

In this paper we seek not to demonstrate how image segmentation can be employed to a particular image noise reduction algorithm, but rather to demonstrate how it can be used as a general tool to improve a variety of techniques.

2. PARTIAL IMAGE SEGMENTATION

A partial segmentation of an image is a decomposition of that image into homogeneous regions. This is distinct from an object-based segmentation, where the goal of the segmentation is to identify distinct physical objects. Clearly a partial segmentation can be used as a tool in developing a complete segmentation, but this is not the objective here.

Evidently our segmentation must be applied to a noisy image, and so must be robust to noisy environments. The scheme we have developed is tailored with this in mind.

There is a range of potential image segmentation schemes that can be adopted. The most suitable techniques for this application are based on morphological operators, being robust to noise and preserving edges. The particular technique we shall consider is based on the watershed algorithm and is discussed in the sequel.

2.1 Partial Image Segmentation Based on the Watershed Algorithm

One of the most widely used techniques for performing a partial segmentation is the watershed algorithm [7]. A watershed breaks an image into segments that correspond to catchment basins. Each catchment basin is a region around a local extrema, defined such that every point in the catchment basin is connect to the extremal point by a path that is monotonic.

The watershed algorithm is generally applied not to the original image, but to the spatial derivative of the image [7], which, for example, can be defined as:

$$G_{m,n} = \frac{1}{2}\sqrt{\left(I_{m+1,n} - I_{m-1,n}\right)^2 + \left(I_{m,n+1} - I_{m,n-1}\right)^2}$$

where $I_{m,n}$ is the image value at (m,n). The reason for applying the watershed to the gradient image region (as opposed to the raw image) is that the boundaries of the segmentation better correspond to object boundaries and so their interiors tend to be more homogeneous.

In our experience a more effective method for constructing the derivative in this application is to use the morphological gradient:

$$\tilde{G}_{m,n} = \max\left\{I_{m,n} \in \mathcal{N}_{m,n}\right\} - \min\left\{I_{m,n} \in \mathcal{N}_{m,n}\right\} \quad (1)$$

where $\mathcal{N}_{m,n}$ is a neighbourhood centred on the $(m,n)^{\text{th}}$ pixel, in our work we have used a 3×3 region.

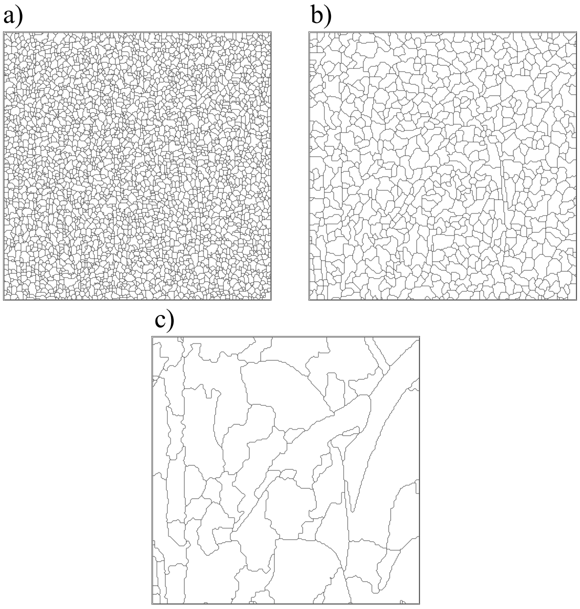


Figure 1: Segmentations of noisy Lena (σ_n=15) using the watershed algorithm a) using unsmoothed gradient b) & c) using smoothed gradient based on the λ-max operator (also see Figure 5).

The segmentations generated by a watershed algorithm are normally vastly over-segmented, that is to say they contain too many small regions. In order to counter this effect we apply an additional smoothing operator to the gradient image generated by the application of (1). The chosen method is the λ-max operator [8].

The λ-max operator consists of a process of reducing local extrema in the image. By repeating the process generates a sequence of smoothed images from the original.

The results of just such segmentations applied to the familiar image of Lena contaminated by additive white Gaussian noise with a standard deviation (σ_n) of 15 are shown in Figure 1. The effectiveness of the λ-max operator as a method of smoothing the (morphological) gradient to mitigate over-segmentation is apparent.

By increasing λ (and hence the degree to which the gradient image is smoothed) one can, indirectly, control the number of segments generated by the watershed algorithm.

We make no claims that the segmentations used in this paper have particularly good qualities as segmentations *per se*. Rather they are efficient schemes that produce adequate segmentations for our purposes.

3. WAVELET NOISE REDUCTION

This section will briefly provide some details of the specific wavelet noise reduction scheme utilised in this work. The choice of a particular wavelet scheme is not critical; the technique discussed here is one that we have found to perform well on a range of images. However the principles we shall describe can be applied to any undecimated wavelet based method (and we believe with some modification can be applied to decimated schemes as well).

We employ an undecimated wavelet transform that is based on analysis filters ($H_0(z)$ and $H_1(z)$) with the transfer functions:

$$H_0(z) = \left(1\text{-}9z^{-2}+16z^{-3}\text{-}9z^{-4}+z^{-6}\right)/32$$
$$H_1(z) = \left(\text{-}1+9z^{-2}+16z^{-3}+9z^{-4}\text{-}z^{-6}\right)/32$$

This decomposition has the property that the synthesis stage simply consists of summing the wavelet components, so no synthesis filters are necessary.

The thresholding technique used was the soft threshold function, $f_{soft}(x;\theta)$ defined by:

$$f_{soft}(x;\theta) = \begin{cases} sign(x)\left(|x|-\theta\right) & |x|>\theta \\ 0 & |x|<\theta \end{cases}$$

This thresholding function depends on the parameter θ which needs to be selected according to measurable image properties. One method for achieving this can be found in []. This method first consists of estimating σ_n using the median absolute deviation (MAD) of the highest frequency component, specifically:

$$\hat{\sigma}_n = 1.483\, med\left\{|W_J|\right\}$$

where $med\{\ \}$ is the median operator and W_J is the highest frequency (smallest scale) wavelet component. An estimate of the variance of the noise free image in the j^{th} wavelet component $\hat{\sigma}_{s,j}$ is defined as

$$\hat{\sigma}_{s,j} = \max\left\{0, \sqrt{\frac{1}{MN-1}\sum_{m,n} W_j^2}\right\}$$

where M and N are the number of rows and columns in the image, W_j is the j^{th} wavelet component. The thresholding parameter for a particular wavelet component is defined as:

$$\theta_j = \frac{\sigma_n^2}{\sigma_x}$$

This method can be applied to the complete wavelet component or can be applied adaptively as described in [5].

4. INCORPERATING SEGMENTATIONS IN WAVELET NOISE REDUCTION

The method we proposed can be viewed as an extension to that suggested in [5] for a decimated wavelet transform, where a pixel's context was used to determine a suitable thresholding value. Here we suggest that the use of segmentation can be used to provide local information about the noise free image statistics and so allow one to adapt the noise reducer's characteristics to the particular local statistics of the image.

This is achieved by projecting the segmentation on to each wavelet component, as shown in Figure 2. Our technique then simply requires one to estimate the image variance over each individual segment, which allows one to compute an appropriate thresholding level, θ, for each segment of the image for each wavelet component.

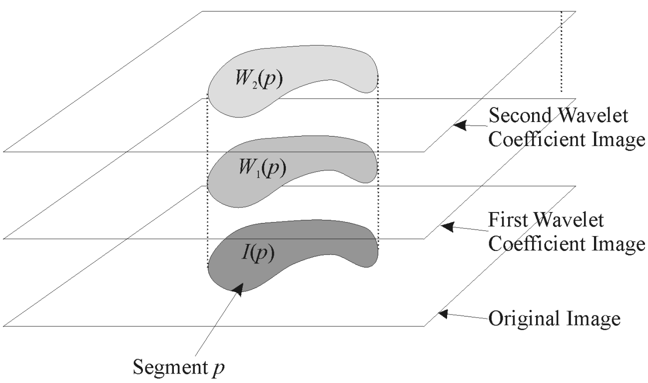


Figure 2: Projecting the segmentation on to each wavelet component.

This adaptive thresholding scheme allows the noise reducer to attenuate the noise more heavily in regions where there is little detail in the original and simultaneously means that in highly textured areas the noise is reduced by a lesser amount.

5. RESULTS

In this section we provide simulation results detailing the performance of the algorithm presented in this paper when applied to a small set of images. In each case the images are corrupted with additive Gaussian noise with a controlled variance. In these trials a noise variance of 15 has been used.

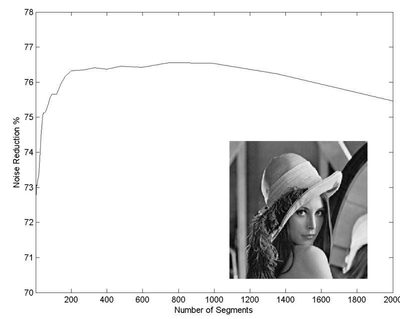
Figure 3 plots the reduction in mean squared error (MSE) between the original (noisy) image $I_{m,n}$ and enhanced image $E_{m,n}$ as a percentage of the original MSE, that is the performance metric Ψ defined as

$$\Psi = 100\frac{\sigma_n^2 - MSE_e}{\sigma_n^2}, \quad MSE_e = \frac{1}{MN}\sum_{m,n}\left(E_{m,n} - \tilde{I}_{m,n}\right)^2$$

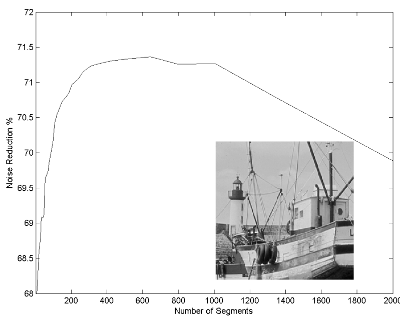
where $\tilde{I}_{m,n}$ is the pristine image, i.e. the image before noise is added.

Figure 3 shows how the reduction in MSE varies as the number of segments in the image increases. In this configuration the number of segments is controlled by the number of applications of the λ-max operator. In each frame of Figure 4 there is a thumbnail plot of the pristine image, so the reader can see the (familiar) original images.

a)



b)



c)

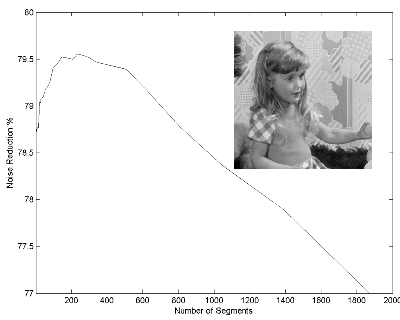


Figure 3: Performance of the algorithm for three different images: a) Lena, b) Boats, c) Girl

Note that the value on the left-hand edge of this plot, corresponding to a single segment is equivalent to the performance of the "standard" method, where no segmentation scheme has been used. The fact that in each case the curve increases significantly from this starting point betrays the fact that applying the segmentation provides an additional performance advantage over conventional methods.

In each case the curves in Figure 3 reach a maximum value whereupon the performance of the algorithm decreases. This is believed to be due to the fact that when there are a large number of segments, each of them is small and the statistics of the data in each segments are poorly estimated. Presently it is not feasible to directly estimate this maximum since to do so one needs knowledge of the pristine image (which in practice one does not have).

Figure 4 provides an example of a pristine image, noisy image and an enhanced image. It is evident that this approach introduces no perceptually perturbing artefacts.

Figure 4: Example images: a) Lena original, b) Lena noisy (σ_n=15) c) Enhanced

6. CONCLUSIONS

This paper has demonstrated how the use of a partial segmentation can improve the performance of image noise reduction algorithms based on decimated wavelet transforms. The principles extolled are generic; not being tailored to any particular noise reduction scheme. The method used to construct the segmentation has not been optimised for this particular application, for example we believe that the use of texture during the segmentation phase could be of considerable benefit. Even under these unfavourable conditions the scheme is able to produce significant improvements in the performance of the algorithm.

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