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A Novel Approach of Watershed Segmentation of Noisy Image Using Adaptive Wavelet Threshold

Nilanjan Dey[#1], Arpan Sinha[#2], Pranati Rakshit[#3]

[#1]IT Department, JIS College of Engineering, Kalyani, Nadia-741235, West Bengal, India
[#2]CSE Department, JIS College of Engineering, Kalyani, Nadia-741235, West Bengal, India
[#3]CSE Department, JIS College of Engineering, Kalyani, Nadia-741235, West Bengal, India

Abstract — **Segmentation of adjoining objects in a noisy image is a challenging task in image processing. Natural images often get corrupted by noise during acquisition and transmission. Segmentation of these noisy images does not provide desired results, hence de-noising is required. In this paper, we tried to address a very effective technique called adaptive wavelet thresholding for de-noising, followed by Marker controlled Watershed Segmentation.**

Keywords— **Wavelet, De-noising, Marker controlled Watershed Segmentation, Bayes Soft threshold**

I. INTRODUCTION

Image Segmentation is a technique to distinguish objects from its background and altering the image to a much distinctive meaning and promoting easy analysis.

One of the popular approaches is the region based techniques, which partitions connected regions by grouping neighboring pixels of similar intensity levels. On the basis of homogeneity or sharpness of region boundaries, adjoining regions are merged. Over-stringent criteria create fragmentation; lenient ones ignore blurred boundaries and overlap.

Marker-based watershed transform is based on the region based algorithms for segmentation by taking the advantage of multi-resolution and multi-scale gradient algorithms.

One of the most conventional ways of image de-noising is using linear filters like Wiener filter. In the presence of additive noise the resultant noisy image, through linear filters, gets blurred and smoothed with poor feature localization and incomplete noise suppression. To overcome these limitations, nonlinear filters have been proposed like adaptive wavelet thresholding approach.

Adaptive wavelet thresholding approach gives a very good result for the same. Wavelet Transformation has its own excellent space-frequency localization property and thresholding removes coefficients that are inconsiderably relative to some adaptive data-driven threshold.

II. DISCRETE WAVELET TRANSFORMATION

The wavelet transform describes a multi-resolution decomposition process in terms of expansion of an image onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization property. Applying DWT in 2D images corresponds to 2D filter image processing in each dimension. The input image is divided into 4 non-overlapping multi-resolution sub-bands by the filters, namely LL1 (Approximation coefficients), LH1 (vertical details), HL1 (horizontal details) and HH1 (diagonal details). The sub-band (LL1) is processed further to obtain the next coarser scale of wavelet coefficients, until some final scale "N" is reached. When "N" is reached, we'll have 3N+1 sub-bands consisting of the multi-resolution sub-bands (LLN) and (LHX), (HLX) and (HHX) where "X" ranges from 1 until "N". Generally most of the Image energy is stored in these sub-bands.

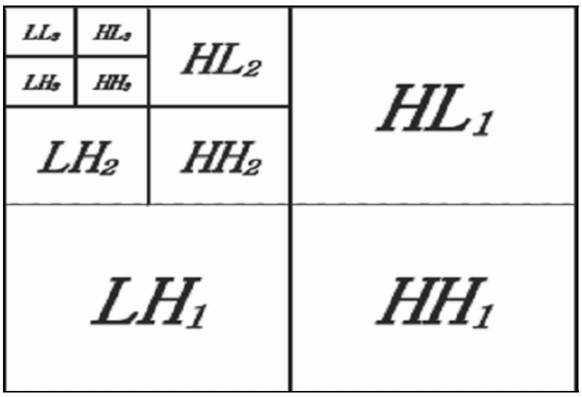


Figure1. Three phase decomposition using DWT.

The Haar wavelet is also the simplest possible wavelet. Haar wavelet is not continuous, and therefore not differentiable. This property can, however, be an advantage for the analysis of signals with sudden transitions.

III. Wavelet Thresholding

The concept of wavelet de-noising technique can be given as follows. Assuming that the noisy data is given by the following equation,

X (t) = S (t) + N (t) (1)

Where, S (t) is the uncorrupted signal with additive noise N (t). Let W (.) and W^{-1}(.) denote the forward and inverse wavelet transform operators.

Let D (., λ) denote the de-noising operator with threshold λ. We intend to de-noise X (t) to recover Ŝ (t) as an estimate of S (t).

The technique can be summarized in three steps

Y = W(X) (2)

Z = D(Y, λ) (3)

Ŝ = W^{-1} (Z) (4)

D (., λ) being the thresholding operator and λ being the threshold.

A signal estimation technique that exploits the potential of wavelet transform required for signal de-noising is called Wavelet Thresholding [3]. It de-noises by eradicating coefficients that are extraneous relative to some threshold.

There are two types of recurrently used thresholding methods, namely hard and soft thresholding [4, 5].

The Hard thresholding method zeros the coefficients that are smaller than the threshold and leaves the other ones unchanged. On the other hand soft thresholding scales the remaining coefficients in order to form a continuous distribution of the coefficients centered on zero.

The hard thresholding operator is defined as

D (U, λ) = U for all |U|> λ

Hard threshold is a keep or kill procedure and is more intuitively appealing. The hard-thresholding function chooses all wavelet coefficients that are greater than the given λ (threshold) and sets the other to zero. λ is chosen according to the signal energy and the noise variance (σ^2)

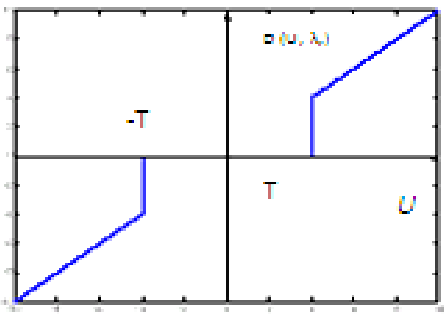


Figure 2. Hard Thresholding

The soft thresholding operator is defined as

D (U, λ) = sgn (U) max (0, |U| - λ)

Soft thresholding shrinks wavelets coefficients by λ towards zero.

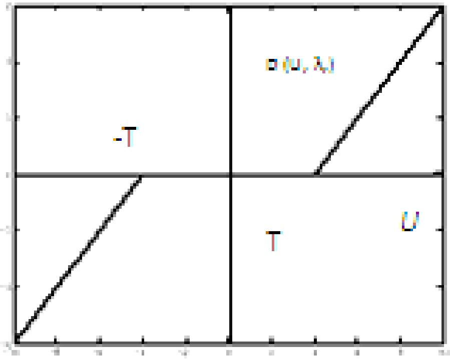


Figure 3. Soft Thresholding

IV. Bayes Shrink (BS)

Bayes Shrink, [6, 7] proposed by Chang Yu and Vetterli, is an adaptive data-driven threshold for image de-noising via wavelet soft-thresholding. Generalized Gaussian distribution (GGD) for the wavelet coefficients is assumed in each detail sub band. It is then tried to estimate the threshold T which minimizes the Bayesian Risk, which gives the name Bayes Shrink.

It uses soft thresholding which is done at each band of resolution in the wavelet decomposition. The Bayes threshold, T_B, is defined as

$$T_B = \sigma^2 / \sigma_s \quad (5)$$

Where σ^2 is the noise variance and σ_s^2 is the signal variance without noise. The noise variance σ^2 is estimated from the sub band HH1 by the median estimator

$$\hat{\sigma} = \frac{median\left(\left\{\left| g_{j-1,k} \right| : k = 0,1,\ldots,2^{j-1}-1\right\}\right)}{0.6745} \quad (6)$$

where $g_{j-1,\ k}$ corresponds to the detail coefficients in the wavelet transform. From the definition of additive noise we have

w(x, y) = s(x, y) + n(x, y)

Since the noise and the signal are independent of each other, it can be stated that

$$\sigma^2_w = \sigma_s^2 + \sigma^2$$

σ^2_w can be computed as shown below:

$$\sigma^2_w = \frac{1}{n^2} \sum_{x,y=1}^{n} w^2(x, y)$$

The variance of the signal, σ_s^2 is computed as

$$\sigma_s = \sqrt{\max(\sigma^2{}_w - \sigma^2, 0)} \;.$$

With σ^2 and $\sigma^2{}_s$, the Bayes threshold is computed from Equation (5).

V MARKER CONTROLLED WATERSHED SEGMENTATION

Marker-Controlled Watershed Segmentation Watershed transform originally proposed by Digabel and Lantuejoul is widely endorsed in image segmentation [7]. Watershed transform can be classified as a region-based image segmentation approach, results generated by which can be taken as pre-processes for further Image analysis.

Watershed Transform [8, 9] draws its inspiration from the geographical concept of Watershed. A Watershed is the area of land where all the water that is under it or drains off of it goes into the same place. Simplifying the picture, a watershed can be assumed as a large bathtub. The bathtub defines the watershed boundary. On land, that boundary is determined topographically by ridges, or high elevation points. The watershed transform computes the catchment basins and ridgelines in a gradient image and generates closed contours for each region in the original image.

A potent and flexible method for segmentation of objects with closed contours, where the extremities are expressed as ridges is the Marker-Controlled Watershed Segmentation. In Watershed Segmentation, the Marker Image used is a binary Image comprising of either single marker points or larger marker regions. In this, each connected marker is allocated inside an object of interest. Every specific watershed region has a one-to-one relation with each initial marker; hence the final number of watershed regions determines the number of markers. Post Segmentation, each object is separated from its neighbours as the boundaries of the watershed regions are arranged on the desired ridges. The markers can be manually or automatically selected, automatically generated markers being generally preferred.

VI. PROPOSED METHOD

Step 1. Perform 2-level Multi-wavelet decomposition of the image corrupted by Gaussian noise.

Step 2. Apply Bayes–Soft thresholding to the noisy coefficients.

Step 3. Apply Marker Controlled Watershed Segmentation on the de-noised image.

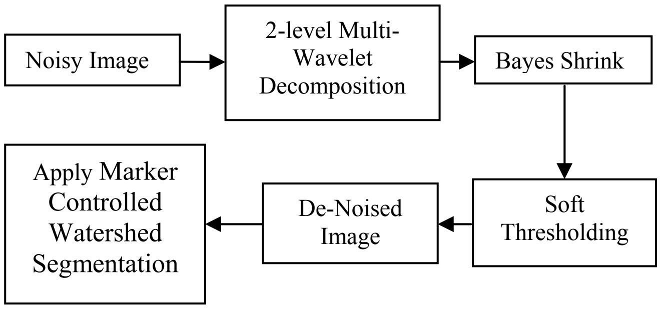


Figure 4

VII. RESULT AND DISCUSSIONS

Signal-to-noise ratio can be defined in a different manner in image processing where the numerator is the square of the peak value of the signal and the denominator equals the noise variance. Two of the error metrics used to compare the various image de-noising techniques is the Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR).

Mean Square Error (MSE):

Mean Square Error is the measurement of average of the square of errors and is the cumulative squared error between the noisy and the original image.

$$\text{MSE} = \frac{1}{MN} \sum_{y=1}^{M} \sum_{x=1}^{N} [I(x,y) - I'(x,y)]^2$$

Peak Signal to Noise Ratio (PSNR):

PSNR is a measure of the peak error. Peak Signal to Noise Ratio is the ratio of the square of the peak value the signal could have to the noise variance.

PSNR = 20 * log10 (255 / sqrt (MSE))

A higher value of PSNR is good because of the superiority of the signal to that of the noise.

MSE and PSNR values of an image are evaluated after adding Gaussian [10, 11]. The following tabulation shows the comparative study based on Wavelet thresholding techniques [12] of different decomposition levels.

TABLE 1

Noise Type	Wavelet	Thres-holding	Level of Decom-position	MSE	PSNR
Gaussian	Haar	Soft	1	0.052	35.59
			2	0.043	35.77
		Bayes Soft	1	0.060	35.28
			2	0.041	36.20

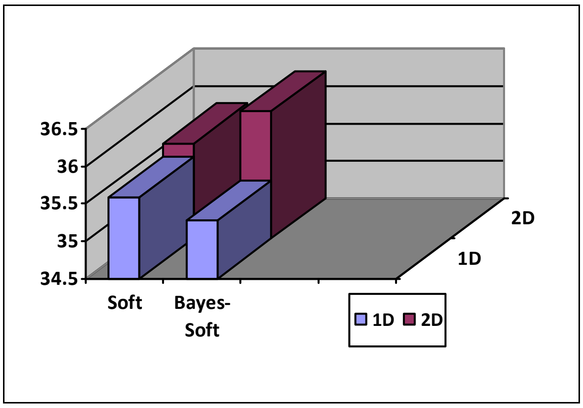
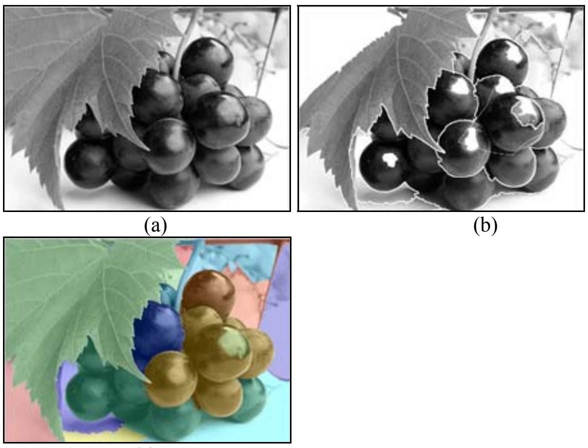


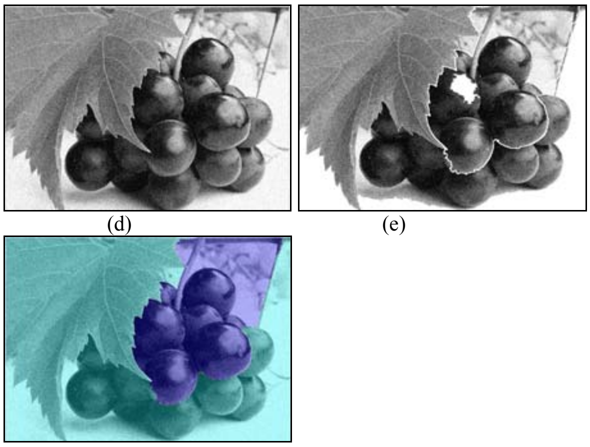
Figure 5. Soft vs. Bayes Soft Threshold



(a) (b) (c)

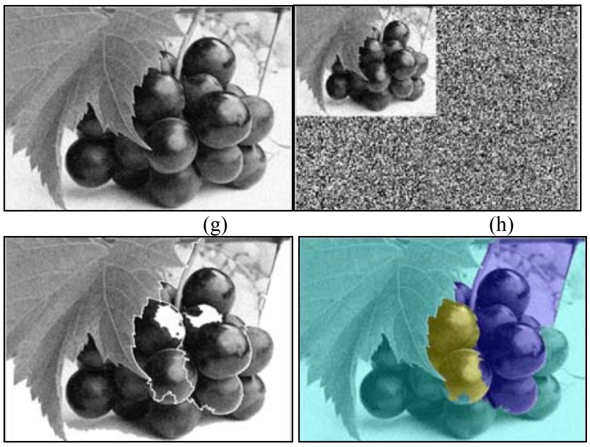
(a)Original Image (b) Markers and object boundaries superimposed on original image (c) Level RGB superimposed transparently on original image

Figure 6. Segmentation of Original Image



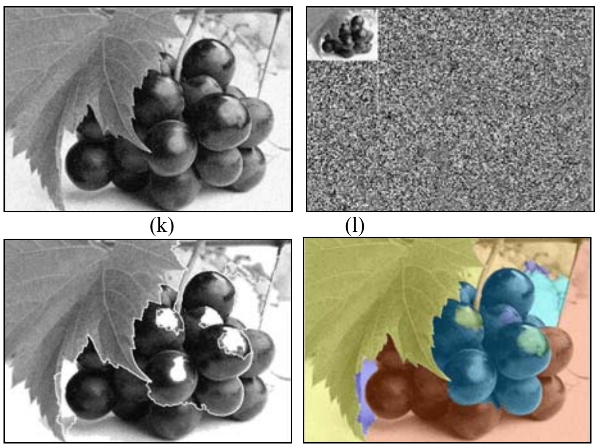
(d) (e) (f)

(d)Noisy Image (e) Markers and object boundaries superimposed on Noisy image (f) Level RGB superimposed transparently on Noisy image
Figure 7. Segmentation of noisy Image



(g) (h) (i) (j)

(g) Noisy image (Gaussian) (h) First level DWT decomposed and soft threshold noisy image (i) Markers and object boundaries superimposed on de-noised image (j) Level RGB superimposed transparently on de-noised image
Figure 8. Segmentation of Noisy image using 1st level DWT decomposition and Soft Threshold



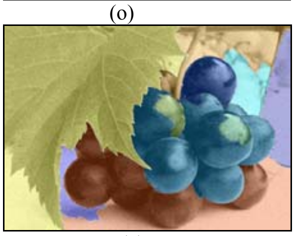
(k) (l) (m) (n)

(k) Noisy image (Gaussian) (l) 2nd level DWT decomposed and soft threshold noisy image (m) Markers and object boundaries superimposed on de-noised image (n) Level RGB superimposed transparently on de-noised image

Figure 9. Segmentation of Noisy image using 2nd level DWT decomposition and Soft Threshold.

(o)

(p)



(q)

(o) Noisy image (Gaussian) (p) Markers and object boundaries superimposed on Bayes soft threshold de-noised image (q) Level RGB superimposed transparently on de-noised image

Figure 10. Segmentation of Noisy image using 2nd level DWT decomposition and Bayes Soft Threshold.

VIII. CONCLUSION

Basically, the Bayes soft thresholding method is used to analyse the methods of the de-noising system for different levels of DWT decomposition because of its better performance than other de-noising methods than only soft thresholding. This paper shows that using Bayes soft threshold wavelet on the region based Watershed Segmentation on noisy image gives a very effective result.

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