IMAGE DENOISING USING SPATIAL CONTEXT MODELING OF WAVELET COEFFICIENTS

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ABSTRACT

The choice of threshold in wavelet based image denoising is very critical. The universal threshold is a global threshold utilized for denoising the wavelet coefficients. An effective approach for the estimation of universal threshold based on spatial context modeling of the wavelet coefficients has been proposed. Spatial context modeling involves determination of the correlated pixels within a local neighborhood of the pixel to be denoised. Thus the threshold determination depends on the pixel characteristics and not on the size of the image to be denoised. The spatial context information of the wavelet coefficients are computed using the range filter employed in the formation of bilateral filter. Experiments on several Gaussian noise corrupted images show that the proposed method outperforms other thresholding methods such as VisuShrink, SureShrink and BayesShrink.

Index Terms— Discrete wavelet transform, Undecimated wavelet transform, Bilateral filtering, Spatial context modeling, Adaptive VisuShrink.

1. INTRODUCTION

Noise removal is the most common and important preprocessing step in image processing applications. The main objective of denoising is to recover the best estimate of the original image from its noisy version. The denoising of a natural image corrupted by Gaussian noise is an abiding problem in signal processing. In this paper, we will deal with spatial context modeling and its application to image denoising. Wavelet domain image denoising methods are most popular among the effective denoising procedures. Denoising by wavelet thresholding is a three step process consisting of a linear forward wavelet transform, a non-linear shrinkage denoising and a linear inverse wavelet transform. Thresholding is a nonlinear technique, yet it is very simple because it operates on one wavelet coefficient at a time.

The main advantage of the wavelet thresholding schemes is the decorrelating property of the wavelet transform which helps in distinguishing the noisy coefficients from the signal coefficients. The image in wavelet domain is decomposed into approximation and detail subbands at various scales. The detail coefficients are processed with soft [1] or hard thresholding to estimate the signal components. Various threshold selection strategies have been proposed for effective denoising. The customary methods among them are VisuShrink [2], SureShrink [3], BayesShrink [4] and NeighShrink [5]. VisuShrink uses the well known universal threshold. SureShrink and BayesShrink utilize subband adaptive threshold hence yield better performance compared to VisuShrink. The universal threshold (λ) proposed by Donoho and Johnstone [2], exists as the crux for most of the wavelet thresholding schemes.

In determining the threshold there is always a trade-off between the closeness of fit and smoothness. A smaller threshold will yield a result closer to the input image, but will still contain some noise. Though a larger threshold yields a smoother image, yet leads to loss of singularities causing blur and artifacts. This persuaded us to develop a subband adaptive threshold determination method based on the spatial context modeling of the wavelet coefficients.

Discrete wavelet transform (DWT) is the most widely used wavelet transform algorithm for image compression. In case of image denoising, the DWT based approach leads to various artifacts mainly due to the loss of translation invariance property [6]. This led to the use of a new translation invariant or undecimated wavelet transform [7] approach for image denoising. There are many variations of undecimated wavelet transform used for denoising applications. Recently we proposed an undecimated wavelet transform (UDWT) based approach for denoising magnetic resonance images [8]. The proposed UDWT approach performs efficiently in comparison to DWT and stationary wavelet transform (SWT) based approaches. In this work, we will be using the UDWT for denoising natural images.

Spatial context modeling involves the estimation of the wavelet coefficient values based on their neighboring coefficients [9]. Context modeling allows us to group pixels of similar nature within a larger neighborhood region. In this work we have estimated the relationship among the neighboring coefficients using the range parameter of the bilateral filter [10]. This helps to determine the number of similar coefficients to the coefficient to be denoised and thus assists in estimating the threshold for denoising. The proposed method is evaluated using root mean square error (RMSE) and structural similarity index (SSIM) [11] as quality metrics.

(a) Original (b) Noisy

(c) VisuShrink (d) SureShrink

(e) BayesShrink (f) Adaptive VisuShrink

Fig. 1: Illustration of image denoising results for Girl image ($\sigma_n = 0.03$).

2. PROPOSED METHOD

2.1. VisuShrink

VisuShrink method is based on the soft shrinkage rule using universal threshold (λ) proposed by Donoho and Johnstone [2]. Regardless of the shrinkage function the threshold is estimated by,

$$\lambda = \sigma_n \sqrt{2 \log N} \tag{1}$$

where σ_n is the estimated noise variance and N denotes the data length. In order to estimate λ we need to know the noise variance σ_n a priori. σ_n value is estimated using the formula used in [2],

$$\hat{\sigma}_n = \frac{MAD\,|D_i|}{0.6745} \tag{2}$$

where MAD is the median absolute deviation and D_i represents the detail coefficients of the finest level of decomposition. The λ value estimated by (1), is data size dependent (N). The proportionality of the threshold to N assumes that, the smoothness of the signal is large if there are more number of samples. It implies that the data is assumed to be sufficiently smooth with in its range and is optimum in mean square error sense as $N \to \infty$. Therefore, the universal threshold aims towards adapting to the smoothness of the data rather than the closeness of fit. The threshold selection holds good for smooth regions and strong edge structures in the image. The small regions and weak edge structures refutes the asymptotic assumption and so, the threshold remains too high to pass these coefficients this leads to more visually smooth result [12] .

Table 1: Comparison of RMSE and SSIM values obtained for denoising different test images using various thresholding schemes.

Results for gray scale images								
	Barbara							
σ_n	VisuShrink		SureShrink		BayesShrink		Adaptive VisuShrink	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
0.01	0.0222	0.9332	0.0111	0.9536	0.0204	0.9491	0.0104	0.9647
0.03	0.0422	0.8318	0.0273	0.8938	0.0266	0.9019	0.0266	0.9037
0.05	0.0527	0.7631	0.0376	0.8222	0.0375	0.8293	0.0370	0.8367
0.07	0.0605	0.7118	0.0478	0.7645	0.047	0.7655	0.0467	0.7689
0.1	0.0667	0.6522	0.0623	0.6789	0.0601	0.6818	0.0559	0.6933
	Cameraman							
σ_n	VisuShrink		SureShrink		BayesShrink		Adaptive VisuShrink	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
0.01	0.0188	0.9408	0.0087	0.9607	0.0125	0.9551	0.0115	0.9684
0.03	0.0352	0.8643	0.024	0.895	0.0214	0.9012	0.0204	0.9064
0.05	0.044	0.8128	0.0338	0.8381	0.0316	0.8396	0.0305	0.8444
0.07	0.0525	0.7597	0.0435	0.7814	0.0418	0.7841	0.0400	0.7880
0.1	0.0596	0.6647	0.0554	0.6875	0.0513	0.6959	0.0493	0.6975
	Girl							
σ_n	VisuShrink		SureShrink		BayesShrink		Adaptive VisuShrink	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
0.01	0.0224	0.9432	0.0108	0.9688	0.0204	0.9561	0.0129	0.9677
0.03	0.0286	0.8946	0.0233	0.9049	0.0227	0.9085	0.0224	0.9107
0.05	0.0347	0.8402	0.0331	0.8504	0.0316	0.8539	0.0291	0.8565
0.07	0.0427	0.7955	0.0399	0.8076	0.0389	0.8079	0.0338	0.8110
0.1	0.0491	0.7282	0.0449	0.7434	0.0443	0.7521	0.0420	0.7626
	Pepper							
σ_n	VisuShrink		SureShrink		BayesShrink		Adaptive VisuShrink	
	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM	RMSE	SSIM
0.01	0.0187	0.9231	0.0135	0.9675	0.0150	0.9708	0.0138	0.9737
0.03	0.0244	0.8430	0.0201	0.8688	0.0198	0.8695	0.0194	0.8740
0.05	0.0301	0.8099	0.0276	0.8194	0.0270	0.8266	0.0262	0.8305
0.07	0.0355	0.7625	0.0332	0.7747	0.0327	0.7763	0.0316	0.7883
0.1	0.0424	0.7040	0.0414	0.7205	0.0398	0.7231	0.0394	0.7343

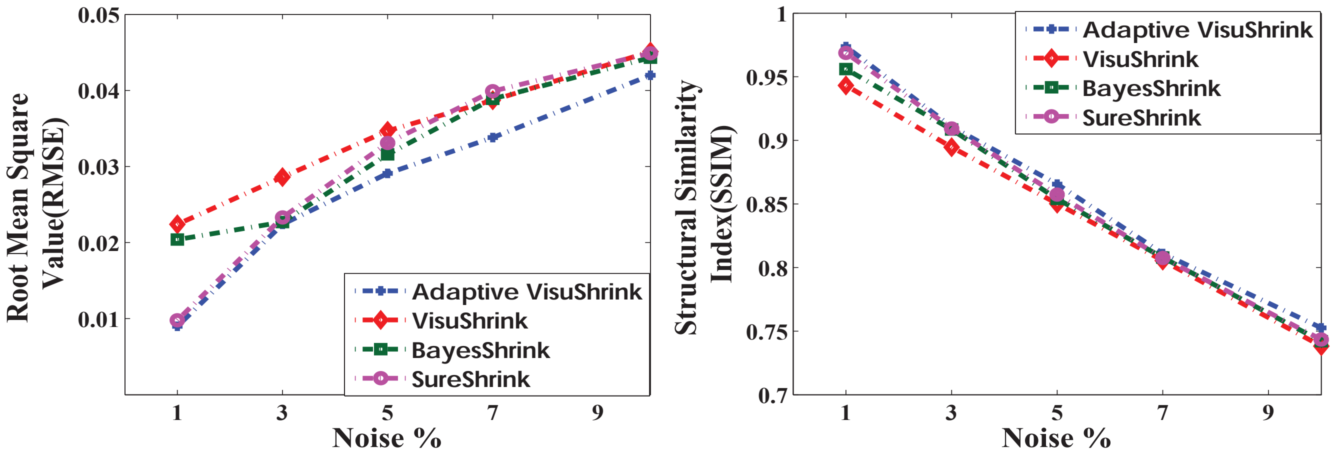

Fig. 2: Results of experiments performed on the Girl image for various noise levels.

2.2. Adaptive VisuShrink

In order to reduce the smoothness and to preserve the weak edges we propose a method to vary the universal threshold based on the spatial context of a pixel to provide better denoising. The spatial context is measured by finding the number of pixels correlated within the local neighborhood of a scaling coefficient, whose corresponding wavelet coefficient is to be denoised. The correlation is computed using the range kernel defined in bilateral filtering method [10].

Assume $i \in \{x-d, ...x+d\}$ and $j \in \{y-d, ...y+d\}$, then for a coefficient $w(x,y)$ in the approximation band its neighbors $w(i,j)$ with-in a window of size $(2d+1)\times(2d+1)$ are obtained. The radiometric similarity between these coefficients are computed using

$$w_s\,(i,j) = e^{\frac{-|w(x,y)-w(i,j)|}{2h^2}} \tag{3}$$

where h is the smoothing parameter and is proportional to the noise variance σ_n. Since, in our approach we use UDWT the approximation and detailed coefficients are of same size in all the levels of decomposition. Hence, estimating the similarity among the pixels from the coarsest level approximation coefficients can be used in their corresponding detail coefficients.

The spatial context S for the coefficient at (x,y) is defined as,

$$S(x,y) = \{\#\,(i,j) : w_s\,(i,j) > \eta\} \tag{4}$$

where $\#$ denotes the cardinality and η is the limiting factor that specifies the maximum permissible value of the radiometric weight for coefficient selection. Therefore, the universal threshold for each coefficient is modified as,

$$\lambda_{xy} = \sigma_n\sqrt{2\log S_{xy}} \tag{5}$$

The threshold defined in Eq. 5 is the adaptive universal threshold and soft thresholding of wavelet coefficients based on this is defined as the adaptive VisuShrink.

(a) Original (b) Noisy
(c) VisuShrink (d) SureShrink
(e) BayesShrink (f) Adaptrive VisuShrink

Fig. 3: Illustration of image denoising results for barbara image ($\sigma_n = 0.07$).

3. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed method is verified by conducting experiments on the standard test images. The experiments were performed on images corrupted with various levels of Gaussian noise. The noisy image is subjected to 3 level decomposition with Haar wavelets in UDWT and then the threshold determined using Eq. 5. The optimal choice of neighborhood size used to determine the correlated neighbors is obtained empirically as 21×21. The denoising result obtained for girl image with noise variance ($\sigma_n = 0.03$) is given in Fig. 1. The image result given in Fig. 1 proves the creditability of the proposed method in comparison with VisuShrink, BayesShrink and SureShrink.

Fig. 2 gives the plot for RMSE and SSIM values for various noise levels of Girl image given in Fig. 1(a). The proposed adaptive VisuShrink based thresholding method yields the least RMSE values and best SSIM values for various noise levels in comparison to the other methods. The denoising results for Barbara image given in Fig. 3 also proves the better performance of our method in comparison to other thresholding techniques. Table I gives the RMSE and SSIM values obtained for different test images for various noise levels. From the values in Table I we can infer that the proposed method produces a better result in comparison to other universal threshold based thresholding methods.

The proposed adaptive VisuShrink method involves more computations in comparison to the existing VisuShrink technique. But, in terms of visual perception and quality metrics it performs well. The small structures and the weak edges are well preserved in the denoised images. This technique can be of huge usage in domains where accuracy is more important than speed. The important advantage of this approach is its simplicity. The extent of smoothing in adaptive VisuShrink can be easily controlled by varying the neighborhood size and the limiting factor η.

4. CONCLUSION

In this paper, we propose adaptive VisuShrink as an improvement to the VisuShrink approach. Spatial context modeling of wavelet coefficients using the radiometric distance measure in bilateral filter helps in determining the adaptive universal threshold. The estimated threshold depends on the neighboring pixel characteristics and not on the size of the image as in universal threshold. This helps in getting a smoother image with edges being preserved. Experimental results confirm the validity of the proposed adaptive VisuShrink technique over the existing wavelet based shrinkage rules.

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