Performance Analysis of Probshrink Image Denoising Method Based on its PSNR Value

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***Abstract* – This paper introduces a new shrinkage method for image denoising. Here we calculate the probability of coefficients with the help of laplacian prior method. Thus on the basis of probability shrinkage of coefficients take place hence it is known as Probshrink. In this paper the performance of Probshrink is analysis by testing this method over some images. Here we came to know what exactly probshrink method and how it is differ form other shrinkage methods. This paper shows the Mean Square Error and PSNR value of Probshrink fr different images and finally compare it with visushrink, bayesshrink, sureshrink. This paper shows the advantages of probshrink over other shrinkage on the basis of results obtained. Here results of probshrink are shown in terms of MSE values and PSNR values. Different comparison curves of different shrinkage methods are also shown in this paper. This paper provide a complete study of Probshrink method along with its results.**

***Keywords* – Probshrink, PSNR, MSE, Different, Testing.**

I. Introduction

With the advancement of new technology in communication field, several researches are take place for the proper transmission of visual information. So that image restoration can be achieved properly. Present days image processing is a major issue in communication field. Basically image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. The purpose of image processing is to observe the objects that are not visible, to create a better image, measures various objects in an image, distinguish the objects in an image. To achieve all these things proper analysis and manipulation of image require which includes data compression and image enhancement. For proper transmission of image require reduction of noise level in image. This process is known as "Denoising Effect". Lots of image denoising methods are already developed based on different shrinkage methods like Sureshrink, Visushrink, Bayesshrink. One of the latest method which developed recently is Probshrink method which have lots of advantage over other shrinkage methods. It provide high PSNR values than other method and remove the noise more efficiently than other method. There is a wide variety of noise types while we focus on the most important types, they are; Gaussian noise, speckle noise, poison noise, impulse noise, salt and pepper noise. The different denoising methods are discussed below.

1.1 Discrete wavelet transform method

It includes decomposition of the image into various sub-bands and then modelling them as independent identically distributed random variables with Gaussian distribution. This method consist of three steps:-

1. Compute the discrete wavelet transforms (DWT).
2. Remove noise from the wavelet coefficients.
3. Reconstruct the enhanced image by using the inverse discrete wavelet transform.

A) Methods of DWT:-

a) Linear filtering
b) Non- linear filtering
c) Wavelet coefficient method
d) Non-Orthogonal wavelet X form

B) Inverse discrete wavelet transform

Decomposition of the data or the image into wavelet coefficients, comparing the detail coefficients with a given threshold value, and shrinking these coefficients close to zero to take away the effect of noise in the data. The image is reconstructed from the modified coefficients. This process is known as the inverse discrete wavelet transform. In the wavelet transform domain noise reduction results from shrinking the noisy coefficient magnitudes ideally, the wavelet coefficients that contain primarily noise should be reduced to negligible values while the ones containing a significant noise-free component should be reduced less. A common shrinkage approach is thresholding [9], where the coefficients with magnitudes below a certain threshold are treated as non significant and are set to zero, while the remaining significant ones are kept unmodified(hard thresholding) or reduced in magnitude (soft thresholding).

1.1.1. Sureshrink: Stein's Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnstone [6]. This method specifies a threshold value t_j for each resolution level j in the wavelet transform which is referred to as level dependent thresholding . The goal of SureShrink is to minimize the mean squared error, defined as

$$\text{MSE} = \frac{1}{n^2}\sum_{x,y=1}^{n}(z(x,y)-s(x,y))^2,$$

where z(x,y) is the estimated signal while s(x,y) is the original signal without noise and n is the size of the signal. SureShrink suppresses noise by thresholding the empirical wavelet coefficients. The SureShrink threshold t^* is defined as

$$t^* = \min\left(t, \sigma\sqrt{2\log n}\right)$$

where t denotes the value that minimizes Stein's Unbiased Risk Estimator, σ is the noise variance and n is the size of the image. SureShrink follows the soft thresholding rule. In soft thresholding the coefficients which are greater than the threshold are shrunk towards zero after comparing them to a threshold value. This method required the minimization of complicated expressions for few nonlinear parameters or the use of parallel block iterative convex programming.

1.1.2. Bayesshrink: BayesShrink was proposed by Chang, Yu and Vetterli [2]. The goal of this method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. The Bayes threshold, t_B, is defined as

$$t_B = \sigma^2 / \sigma_s$$

where σ^2 is the noise variance and σ^2_s is the signal variance without noise. In this method an adaptive data-driven threshold is used for image denoising. The BayesShrink performs better than sure shrink in terms of MSE . The result are much better than visushrink. The sharp features of image are retained. But MSE is considerably lower. This is because sureshrink is subband adaptive.

1.1.3. Visushrink: Visushrink was introduced by Donoho [Do92]. It uses a threshold value 't' that is proportional to the standard deviation of the noise. It follows the hard thresholding rule. It is also referred to as universal threshold and is defined as

$$t = \sigma\sqrt{2\log n}$$

σ^2 is the noise variance present in the signal and n represents the signal size or number of samples. Visushrink does not deal with minimizing the mean squared error . Visushrink is known to yield recovered images that are overly smoothed. This is because Visushrink removes too many coefficients. Another disadvantage is that it cannot remove speckle noise. It can only deal with an additive noise.

II. Proposed Methodology

We can define image denoising as a way to improve the quality of image by removing the noise from it. This process of improving the quality of image by manipulating the noisy image is done with MATLAB software. First we select the original image and then we add the noise in it. After that apply wavelet transform which decompose the image into different coefficients. Then apply thresholding technique on it, and then shrunk the coefficients by using Probshrink method. After that perform inverse wavelet transform and get original image without noise. This method is clear through the following flow chart.

2.1 Probshrink

This method is based on the Probability and Laplacian prior. This method estimate the probability of a significant noise free component present in a given wavelet coefficients. The probability is calculated by using laplacian prior for noise free subband data and additive white gaussian noise. Here noise free component is known as signal of interest. For estimating probabilities previous methods based on preliminary coefficient classifications yielding binary masks that were combined with MRF

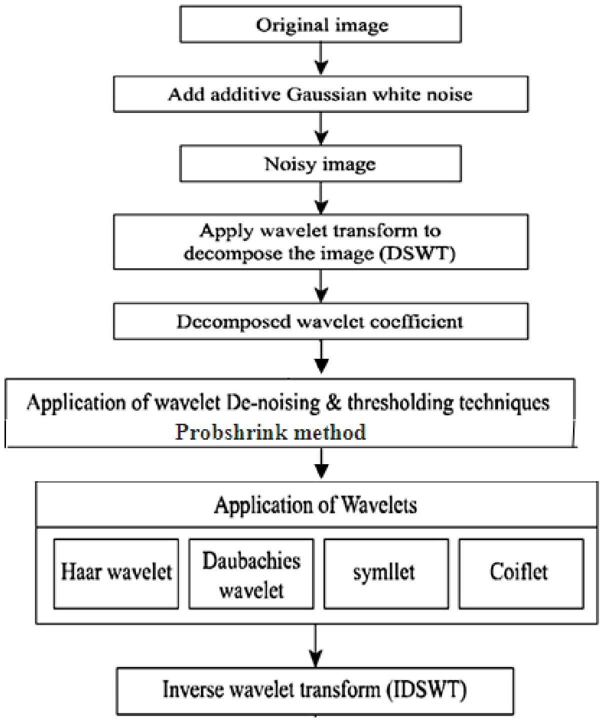

Fig.1. Block diagram of algorithm flow

priors. Probshrink method remove the need of preliminary coefficient classifications and derive the required probability from the generalized Laplacian marginal prior. Advantages of this method is that it does not depend on any preliminary edge detection steps. It is simpler to implement and faster. It give better results than the more complex ones based on MRFs. After finding out probability we apply simple shrinkage rule for performing denoising action according to shrinkage rule the wavelet coefficients that contain noise should be reduced to negligible values while the ones containing a significant noise-free component should be reduced less. On the basis of probability of coefficients it is decided which coefficient is reduces. Probshrink uses soft thresholding method.

2.2 Laplacian prior

It is a continuous probability distribution named after Pierre-Simon Laplace. It is also called the double exponential distribution, since it is a combination of two exponential distributions. The Laplace prior is very similar to the total variation (TV) prior indeed, in one-dimension they are the same and yields reconstructed images that are both quantitatively, and qualitatively, very similar. The Laplace prior yields regularized solutions that lie in the space of bounded variation and we present numerical experiments from both image deblurring and positron emission tomography showing that Laplace prior works well and yields TV like reconstructed images. The benefit of using the Laplace prior is that it follows from concrete distributional assumptions regarding the increments in the unknown image, which can be modified to better fit the specific situation. For a typical image, it makes intuitive sense that the increments will usually be near zero,

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corresponding to areas of smooth variation in image intensity, but will often have large magnitude, corresponding to edges where sharp intensity changes occur. In this method the increments are assumed to be independent and identically distributed Laplace random variables a distribution with heavy tails allowing for large increment values with zero mean. The prior constructed from the Laplace increment model is very similar to the total variation (TV) prior. The Laplace prior yields a regularization scheme with regularized solutions contained in the space of bounded variation. The assumption of Laplacian increments is motivated by the fact that in many signals, the increments sizes are typically small, but outliers (large increments) are not uncommon. Due to the fact that the Laplace distribution has heavy tails, large increments (outliners) are much more probable than if a gaussian increment model is assumed. The resulting prior yields a convergent regularization scheme with solutions lying in the space of bounded variation.

2.2.1 ProbShrink rule for the generalized Laplacian prior

$$f(\beta|H_0) = \begin{cases} B_0 \exp(-\lambda|\beta|^\nu), & \text{if } |\beta| \le T \\ 0, & \text{if } |\beta| > T \end{cases}$$

and

$$f(\beta|H_1) = \begin{cases} 0, & \text{if } |\beta| \le T \\ B_1 \exp(-\lambda|\beta|^\nu), & \text{if } |\beta| > T \end{cases}$$

with normalization constants

$$B_0 = \frac{\lambda\nu}{2\Gamma(\frac{1}{\nu})\Gamma_{inc}\left((\lambda T)^\nu, \frac{1}{\nu}\right)}$$

$$B_1 = \frac{\lambda\nu}{2\Gamma(\frac{1}{\nu})\left[1 - \Gamma_{inc}\left((\lambda T)^\nu, \frac{1}{\nu}\right)\right]}$$

Where Γ_{inc} is the incomplete gamma function. The probability of signal presence amounts to the area under the tails of f(β) for β > T and thus we estimate P(H1) as

$$P(H_1) = 1 - \int_{-T}^{T} f(\beta)d\beta$$

after putting the value of f(β) from above equation the $P(H_1)$ becomes

$$P(H_1) = 1 - \Gamma_{inc}\left((\lambda T)^\nu, \frac{1}{\nu}\right)$$

and thus

$$\mu = \frac{P(H_1)}{P(H_0)} = \frac{1 - \Gamma_{inc}\left((\lambda T)^\nu, \frac{1}{\nu}\right)}{\Gamma_{inc}\left((\lambda T)^\nu, \frac{1}{\nu}\right)}$$

For the laplacian prior v=1, the above expression reduces to

$$\mu = P(H_1)/P(H_0) = \exp(-\lambda T)/[1 - \exp(-\lambda T)].$$

Where μ is the global statistical properties of the coefficients in a given subband . Shrinking of coefficients depend on the probability which is based on μ.

III. Results

There are three goals of the experimental performance evaluation in this Section. Firstly, we wish to investigate the optimal (in terms of mean squared error) choice of the parameter *T*, which specifies the signal of interest in the proposed ProbShrink rule. Secondly, we wish to compare the performance of the resulting shrinkage rules under Laplacian and under generalized Laplacian priors. Finally, we wish to evaluate the performance of these new Bayesian shrinkers with respect to MAP and MMSE estimators and with respect to BayesShrink. Recall that the MAP estimate under the Laplacian prior is soft-thresholding with the threshold $\sigma^2\lambda = \sqrt{2}\sigma^2/\sigma_\beta$ and that BayesShrink is soft-thresholding with the threshold σ^2/σ_β that is for natural images optimal in terms of mean squared error.

Table 1: Comparision of shrinkage techniques in terms of PSNR value with different standard deviations

Image	Vishu-Shrink	Bayes-shrink	Sure-shrink	Prob-shrink
Lena				
σ=10	30.56	33.4106	33.4755	33.758
σ=20	28.75	30.2258	30.0724	30.7206
σ=30	26.78	28.4901	28.3935	28.5313
Barbara				
σ=10	25.72	31.0322	30.6327	32.2263
σ=20	23.91	27.2843	27.2961	27.974
σ=30	22.61	25.2842	25.0969	25.5726

Fig.2. Test images. Top left to right:Airfield, Barbara, Boat Bottom left to right: Couple, Goldhill, lena

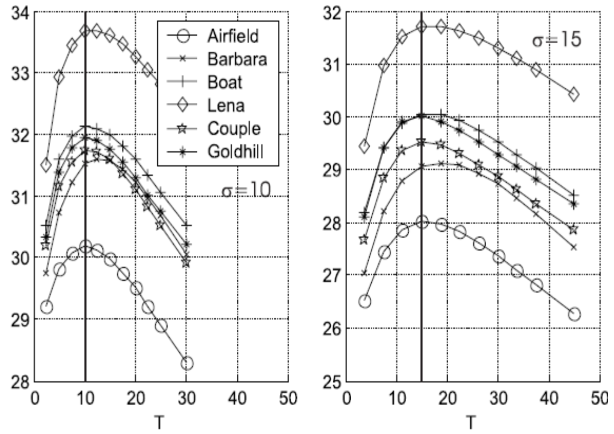

Fig.3. PSNR value of Laplacian Prior

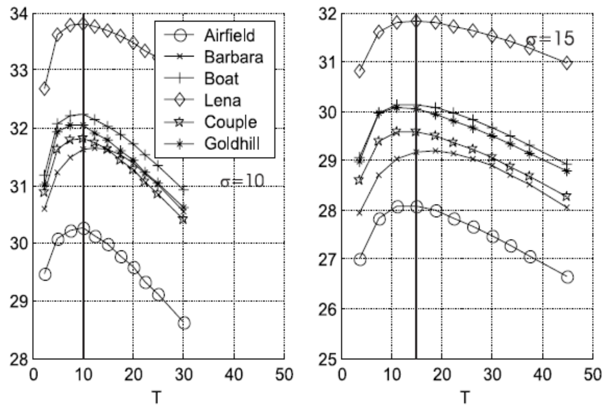

Fig.4. PSNR value of Generalized Laplacian Prior

We used six representative natural images from Fig. 3, which were corrupted by various amounts of artificial additive white Gaussian noise. The experimental results are shown in Fig. 4, Fig. 5 and in Table II, where PSNR denotes the peak signal to noise ratio , where MSE is the mean squared error. The diagrams in Fig. 4 and Fig. 5 demonstrate clearly that for the ProbShrink rule the optimal threshold value is a function of noise level. For both the Laplacian and the generalized Laplacian prior the PSNR peaks at $T = \sigma$. All the following results in this paper correspond to this threshold selection.

Table 2: Input and output MSE values of different images using probshrink techniques for different standard deviation

BARBARA	INPUT MSE	OUTPUT MSE
σ=10	100.24	24.20
σ=20	400.32	58.24
σ=30	900.35	96.87
LENA		
σ=10	100.24	24.20
σ=20	400.32	58.24
σ=30	900.35	96.87

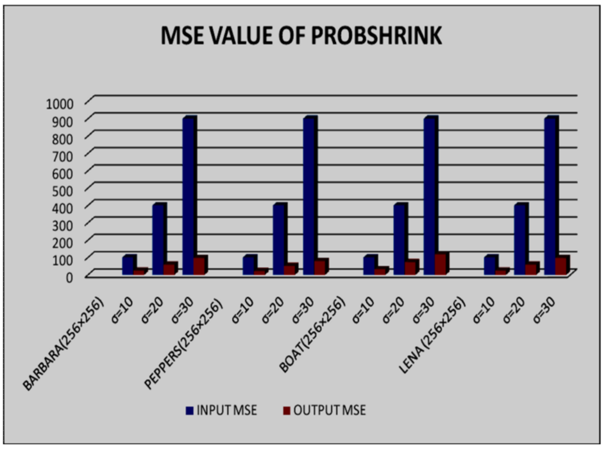

Fig.5. Graphical Representation of MSE value of Probshrink for different images.

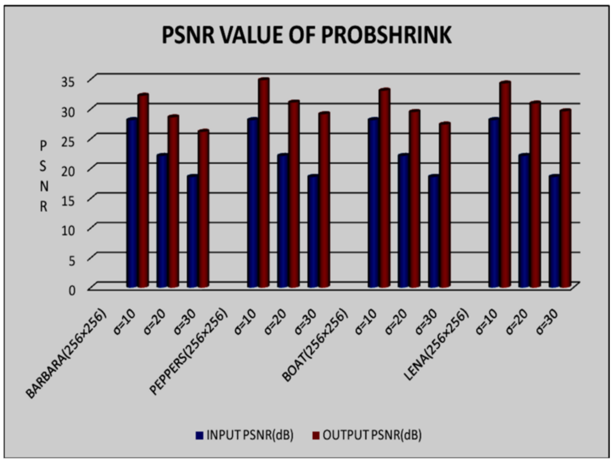

Fig.6. Graphical Representation of PSNR values using Probshrink for different images.

The above curve of MSE and PSNR value is the graphical representation of PSNR and MSE value of Probshrink method which specified in the table 1. We have to tested probshrink method on different images like on Barbara, Lena, Boat, Peppers and calculate their PSNR value and MSE value. Graphical representations show that Probshrink give high value of PSNR and low value of MSE for different images of 256*256 sizes. Probshrink give high PSNR:34.85 and low MSE 21.6 for standard deviation σ =10.Thus this method is suitable for different images.

IV. Conclusion

Finally we concluded that the peak signal to noise ratio (PSNR) of ProbShrink rule with T(Threshold) = σ (standard deviation of noise) is much better than BayesShrink and adaptive Bayesian wavelet shrinkage methods. ProbShrink suppresses noise slightly better than other Shrinkage method while preserving the image details equally well. It provide good visual quality. Since BayesShrink is soft thresholding with the MSE(mean square error) optimum threshold, we can deduce that ProbShrink outperforms soft thresholding with any threshold that is constant per subband, hence ProbShrink yields a slight improvement on all images compared to BayesShrink. ProbShrink also better denoises any multispectral band. The effectiveness of the proposed multiband denoising method results from adapting the wavelet shrinkage to both the interband correlations and to the local statistics in each image band. In other words, the estimated probabilities of signal presence are different in each image band even though they are dependant on information from other bands as well as on the measurements from the given band.

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