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Assessment of noise prohibiting of medical images using hybridization of partical swarm optimization & bivariate shrinkage methods

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ABSTRACT
Denoising of pictures got corrupted by addition of noise signals (generated by no single reason) has invariably a theme of interest for researchers. This paper proposes Associate in Nursingd classifies the potency of an rule supported quantity shrinkage additional optimized by Particle Swarm optimization (PSO).The calculator for undecimated filter bank that incorporate the reconciling sub bands thresholding additional delineated with singal threshold supported denosing performs. The manuscript evaluate recital of medical image denoising by estimate of PSNR, MSE, WPSNR and SSIM. The replication results based on trying the reproduction at MATLAB 2010A platform shows momentous augmentation in alleviation of Gaussian noise, speckle noise, poisson noise and salt & pepper noises from investigational records.

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Introduction

Medical data supported the study of affected scenes in pictures, clinical data; physiological signals square measure the obligatory aspectsin screening, medicine, and treatment. Medical imaging is that the product of development that echoed few decades past because the exponential elevate within the study of medical-Instrumentation and information-exchange. Few merchandise emerged that revolutionized the medical segments were: digital imaging processes for tube-shaped structure, vas and distinction imaging, nuclear medical imaging with single gauge boson emission CT, CT, resonance imaging, antilepton emission pictorial representation and diagnostic ultrasound imaging. the pictures generated from such resources look for the inner structure of animal, subject to the modalities used for image acquisition. The applications of digital pictures aren't finite to one utility. Aerial Communications, artificial Aperture radiolocation, pc assisted picturing, physics area unit few examples that employs digital imaging techniques. The preponderating issue sweet-faced by researchers is that the received quality of digital pictures. The mixture of noise renders pictures to be creaky, corrupted and incomplete in nature [1] throughout the acquisition by camera sensors, receivers, environmental conditions, improper lighting, undesirable read angles etc [2]. The characteristics of creaky pictures visible to naked eyes recognizing, granular and hoary image effects thus the phase of recovery of original or best fitting image has gained hefty attention by researchers in recent years [3]. The image denoising method is that the study of recovery of image by the estimation of desired image from corrupted image [4] [5]. The denoising processes studied mustn't destroy the anatomical details from clinical purpose of read. Thus, proposing of a strong methodology for noise removal that works well for various modalities of medical pictures [8] with the given constraints has invariably been a big challenge for researchers. From the literature of [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25] it will be expressed the quantity of analysis presently going down during this field.

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Proposed Methodology- A new modest non-Gaussian quantity likelihood distribution perform to excellent the statistics of riffle coefficients of natural pictures. The model arrests the dependence amongst a riffle constant & its parent. exploitation Bayesian estimation theory we have a tendency to develop from this model a modest non-linear shrinkage perform for riffle denoising, that take a broad read of sentimental thresholding approach. The new shrinkage perform, that suspend on each the constant & its parent, produces improved results for wavelet-based image denoising. planned PSO-based window choice methodology obtains council range of windows. when the classification of nearest windows denoising is sustained exploitation the previous windows.

- First take a medical image as an input for our Proposed Denoising Approach.
- As a preprocessing step, we apply RGB to GRAY conversion, since most of the digital filters works only on individual single page two dimensional matrix data, not on multi-dimensional data.
- Before Applying our proposed Denoising process, we have to add noise (Any, like Gaussian noise, speckle noise, Poisson noise etc.) in clean medical images with an appropriate value of variance.

The denoising of an image corrupted by white Gaussian noise will be considered, i.e.

$$g = x + n$$

Where n is independent Gaussian noise. We observe g (a noisy signal), and wish to estimate the desired signal x as accurately as possible according to some criteria. In the wavelet domain, if we use an orthogonal wavelet transform, the problem can be formulated as

$$y = w + n$$

Where y is the noisy wavelet coefficient, w is the original coefficient and n is noise, which is independent Gaussian. This is a classical problem in estimation theory. Our aim is to estimate w from the noisy observation, y. The maximum a posteriori (MAP) estimator will be used for this purpose. We use bivariate models for this problem to derive a new MAP estimator.

Here, we modify the Bayesian estimation problem so as to take into account the statistical dependency between adjacent wavelet coefficients. Let w2 represent the parent of w1: (w2 is the wavelet coefficient at the same position as w1, but at the next coarser scale.) Then

$$y1 = w1 + n1$$
$$y2 = w2 + n2$$

Where y1 and y2 are noisy observations of w1 and w2; and n1 and n2 are noise samples.

- The obtained window of pixels are transformed to multiwavelet transformation domain as follows

$$W_i\,(a,b) = F_{GHM}(a,b).w_i(a,b).F^T_{GHM}(a,b)$$
$$W_j\,(a,b) = F_{GHM}(a,b).w_j(a,b).F^T_{GHM}(a,b)$$

Where, $0 \le a \le m-1$, $0 \le b \le n-1$ and mXn indicates the window size.

$F_{GHM}$is the concatenated filter coefficient of GHM multi-wavelet transformation, $W_i$and $W_j$are $w_i$and $w_j$in multi-wavelet domain, respectively.For each W_i,$W_j$that are nearer to $W_i$are selected founded on L2 norm distance ($L2_{ij}$), which can be calculated using

$$L2_{ij} = \sqrt{\sum_{a=0}^{m-1}\sum_{b=0}^{n-1}(|W_i(a,b) - W'_j(a,b)|)^2}$$

Using the $L2_{ij}$, the $W_j$windows that are nearer to theW_i, W'_{L2ij}can be demarcated as $W'_{L2ij} = W_{L2ij} - \phi$, where, $W_{L2ij}$is given as

$$W_{L2_{ij}} = \begin{cases} W'_j & ; \quad if \quad L2_{ij} \le L2_T \\ \phi & ; \quad else \end{cases}$$

The fitness function is given as:

$$f_i(l) = \frac{1}{n_c}\sum_{k=0}^{n_c-1} L2_{ilk}$$

Wher, $f_i(l)$ is the fitness of thel^{th}element generated for the i^{th} window &$L2_{ilk}$ is the L2 norm distance determined between the w_i& the window indexed by the k^{th} atom of the l^{th} element. The $L2_{ilk}$ is determined as follows

$$L2_{ilk} = \sqrt{\sum_{a=0}^{m-1}\sum_{b=0}^{n-1}\left(\left|W_i(a,b) - W'_{r_{ilk}}(a,b)\right|\right)^2}$$

Where, $W'r_{ilk}$ is the window indexed by r_{ilk} that is converted to multi-wavelet transformation domain

- Adjust window size and the corresponding filter for the selected window for bivariate shrinkage function.
- Define number of filtering stages and Symmetric Extension as per the length of filtering stages.
- Apply Farras nearly symmetric filters for orthogonal 2-channel perfect reconstruction filter bank for Forward discrete wavelet transform structure in third module and Kingsbury Q-filters for the dual-tree complex Discrete wavelet transform in fourth module in order to apply forward transform on noise added images.
- After that, We Have to Apply 2D discrete Wavelet transform in third module and 2D dual tree complex discrete wavelet transform in fourth module using the analysis filter bank structure (Low pass and High pass filtering in different circular shift).
- After applying forward transform we have to apply Noise variance estimation procedure by using robust median estimator.
- Before applying inverse transform, we have to calculate bivariate shrinkage function of the image using noisy coefficients, noisy parents and Threshold value estimation.

The standard MAP estimator for w given the corrupted observation y is

$$\hat{w}(y) = argmax_w P_{(w|y)}(w|y)$$

After some manipulations, this equation can be written as

$$\hat{w}(y) = argmax_w P_{(y|w)}(y|w).P_w(w)$$
$$w\ (y) = argmax_w P_n(y-w).P_w(w)$$

From this equation, Bayes rule allows us to write this estimation in terms of the probability densities of noise and the prior density of the wavelet coefficients. In order to use this equation to estimate the original signal, we must know both pdfs. We assume the noise is i.i.d. white Gaussian, and we write the noise pdf as

$$p_n(n) = \frac{1}{2\pi\sigma_n^2}\exp\left(-\frac{n_1^2+n_2^2}{2\sigma_n^2}\right)$$

The same problem as in marginal case appears. What kind of joint pdf models the wavelet coefficients? The joint empirical coefficient-parent histogram can be used to observe $p_w(w)$. The joint histogram, can be computed (Empirical Joint parent-child histogram of wavelet coefficients).

It is hard to find a model for this pdf, but we use the following pdf

$$p_w(w) = \frac{3}{2\pi\sigma^2}exp\left(-\frac{3}{\sigma}\sqrt{w_1^2+w_2^2}\right)$$

With this pdf, w_1 and w_2 are uncorrelated, but not independent. Before going further with this new model, let's consider the case where w_1 and w_2 are assumed to be independent Laplacian, then the joint pdf can be written as

$$p_w(w) = \frac{1}{2\sigma^2}exp\left(-\frac{\sqrt{2}}{\sigma}(|w_1| + |w_2|)\right)$$

Let's continue on developing the MAP estimator given, which is equivalent to

$$\hat{w}(y) = argmax_w log(P_n(y-w)).log(P_w(w))$$

Let's define, $f(x) = log(P_w(w))$

Hence,

$$\hat{w}(y) = arg\,max_w\left[-\frac{(y_1-w_1)^2}{2\sigma_n^2} - \frac{(y_2-w_2)^2}{2\sigma_n^2} + f(w)\right]$$

This is equivalent to solving the following equations together, if $P_w(w)$ is assumed to be strictly convex and differentiable.

$$\frac{y_1-\hat{w}_1}{\sigma_n^2} + f_1(\hat{w}) = 0$$
$$\frac{y_2-\hat{w}_2}{\sigma_n^2} + f_2(\hat{w}) = 0$$

Where f_1 and f_2 represent the derivative of $f(w)$ with respect to w_1 and w_2 respectively.

This rule applies the soft threshold function to y_1 to estimate w_1.

Hence, $f(w)$ can be written as

$$f(w) = log\left(\frac{3}{2\pi\sigma^2}\right) - \frac{3}{\sigma}\sqrt{w_1^2+w_2^2}$$

From this,

$$f_1(w) = -\frac{3w_1}{\sigma\sqrt{w_1^2+w_2^2}}$$

And,

$$f_2(w) = -\frac{3w_2}{\sigma\sqrt{w_1^2+w_2^2}}$$

Table 1: Performance comparison of proposed methodology and its effect on various noise and image type

Image-Barbara	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	37.9248	11.2008	43.1271	0.977244	0.235509
GAUSSIAN NOISE	35.3078	23.1155	38.7427	0.78342	0.132728
SALT & PEPPER NOISE	47.2095	16.2363	47.8016	0.960089	0.118133
SPECKLE NOISE	35.164	23.9279	38.123	0.968154	0.228614
Image-Leena	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	38.8394	10.594	44.088	0.963933	0.206691
GAUSSIAN NOISE	38.3205	18.1	39.5271	0.880729	0.212508
SALT & PEPPER NOISE	48.0804	15.27364	47.9249	0.854926	0.253186
SPECKLE NOISE	35.7653	20.7047	38.6693	0.963108	0.174577
Image-SPECT	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	37.0613	20.1743	41.7958	0.924622	0.128942
GAUSSIAN NOISE	35.5149	21.9926	37.1528	0.689865	0.108839
SALT & PEPPER NOISE	47.8002	17.8571	42.8698	0.898432	0.222314
SPECKLE NOISE	35.7675	25.3103	39.7148	0.849395	0.120501
Image-MRI	PSNR	MSE	WPSNR	SSIM	TIME
POISSON NOISE	35.8795	20.1415	41.5439	0.971004	0.221137
GAUSSIAN NOISE	34.8518	24.7853	38.4314	0.867568	0.211641
SALT & PEPPER NOISE	49.5434	20.8093	43.8133	0.860776	0.196596
SPECKLE NOISE	34.3418	31.1235	39.8567	0.960667	0.225587

The MAP estimator (or "the joint shrinkage function") or simply we can say that the bivariate function can be written as

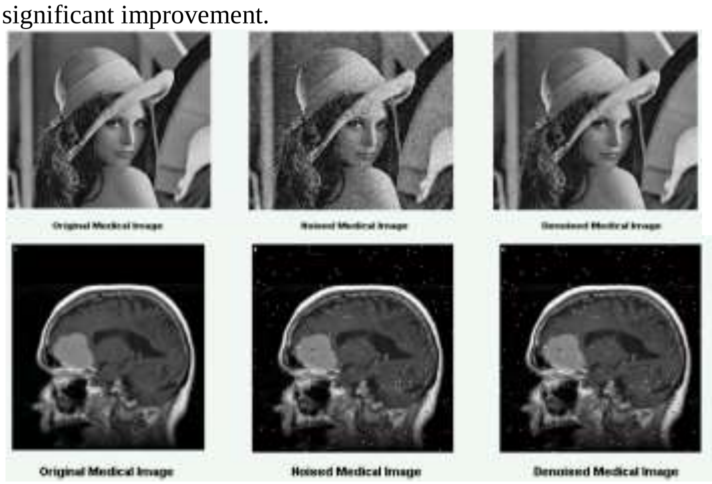
$$\widehat{w_1} = \frac{\left(\sqrt{y_1^2+y_2^2} - \frac{\sqrt{3}{\sigma_n}^2}{\sigma}\right)}{\sqrt{{y_1}^2 + {y_1}^2}} . y_1$$

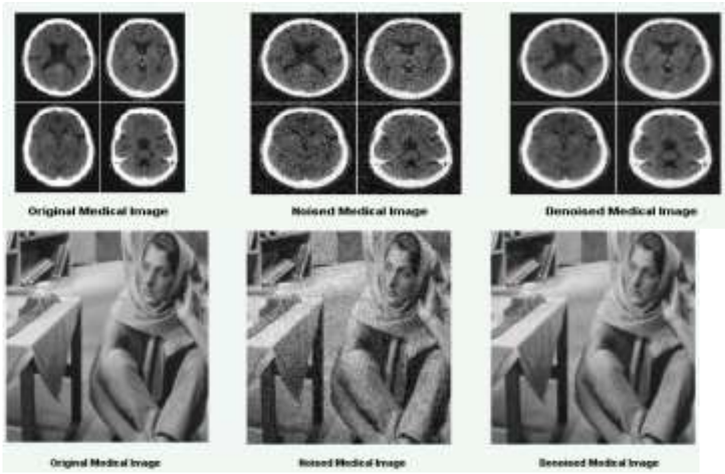
The models which use the independence assumption do not care what the parent value

(y_2) is. For example, in scalar soft thresholding, for all coefficients the threshold value is fixed and independent from other coefficients - if the coefficient is below the threshold value, we make it zero. However the estimated value should depend on the parent value. The smaller the parent value, the greater the shrinkage.

- The Threshold value estimation can only possible with noisy coefficients, noisy parents and signal variance estimation by convoluting noisy coefficients with window filters output.

Result & Discussion- From all the above discussion, data and analysis which carried out for four different images (Salt & pepper, Gaussion, Speckle and Poisson noise) for standard variance of 0.01 and different values of PSNR, MSE, WPSNR, SSIM for various noise types are found. We observed that the test images has shown some improvement in most of the parameter in consideration (PSNR, MSE, WPSNR, SSIMfor various noise type).Image denoising using bivariate shrinkage function and PSO algorithm in all the images has shown a much significant improvement.





(a) (b) (c)

Figure 2: Image (a) original image, (b) Image with Gaussian noise (c) denoised image

Nearly 60% improvement is seen in PSNR, whereas MSE has decreased to nearly 99% after adaptive filters. These improvement has helped to achieve better WPSNR between 17% to 50% improvement in various image type. SSIM has increased in all the noise type,8-79% which means better structural similarity is obtained with the original image.

Conclusion- In this paper, new technique has been given. The projected quantity and PSO primarily based technique approach not solely computationally economical however additionally offers higher performance indicated by performance indices PSNR, MSE, WPSNR, SSIM and time. Finally, it's terminated that the projected approach in terms of PSNR, WPSNR improvement is outperformed. The projected technique optimize the likelihood of low pass constant from every sub band based on quantity of shrinkage is said to signal dependent noise variance. In this paper a replacement technique is projected to mitigate the noise in pictures. consistent with results the novel quantity technique optimized by Particle Swarm improvement is computationally economical and performs considerably superior in performance indices indicated by PSNR, MSE, WPSNR, SSIM and time. Finally, we are able to conclude that in terms of WPSNR and PSNR the projected approach is outperformed.

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