

Hybrid denoising technique for medical images using discrete multi-wavelet transform

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| Keywords | Abstract |
|------------------------------|---|
| Mammogram Images; | <p>Generally, most of the images are corrupted by noise which is solved by denoising techniques in the image processing. For that single thresholding techniques are used which removes the additive random noise. The Gaussian -Multi Wavelet technique is utilized to denoising the Gaussian noise present in the mammogram image which is an efficient method due to the capability to acquire the signal energies in few transforms value. In order to enhance and the noise present in the digital mammographics image, the novel Multi Wavelet techniques are used in this paper. In the first step, image preprocessing is carryout which improves their discrimination of subtle detail and local contrasts. In addition to that edge enhancements and suppressions are accomplished using Multi-Wavelet transforms. We proposed moment based mixed noise reduction technique which decomposes images by discrete Multi-Wavelets after that Improved K-SVD technique is performed by the new threshold values. To removing the single or mixture noises present in the digital mammographic images without affect the information, the proposed technique is implemented. The performance of the proposed method is analyzed based on the objective evaluation parameter such as PSNR, which is compared with different Multi-wavelet base and various neighborhoods sizes. From the experimental result, conclude that the proposed Multi-wavelets techniques improves the quality of the images in subjective and objective evaluations. The subjective performance are analyzed based on the visual quality of the images such as edge sharpening and details of the images.</p> |
| Additive random noise; | |
| Gaussian - Gaussian Mixture, | |
| Multi Wavelet; | |
| Gaussian Noise; | |
| Denoising; | |
| K-SVD; | |
| PSN; | |

1. Introduction

This research work examines the applicability of various Multi-Wavelet base with various neighborhoods sizes, performances of mammographic sample denoising algorithm based on the PSNR. Few years ago, multi-wavelet transform has gotten a many consideration from analysts in a wide range of areas. The continuous and discrete multi-wavelet has demonstrated extraordinary guarantee in such differing areas as signal processing, image compression, computer graphics, pattern recognition and image de-noising to give some examples.

The single-mother and single-orthogonal multi-wavelet functions in the denoising algorithm play a major roles [27]. The Gaussian -Multi Wavelet technique is utilized to denoising the Gaussian noise present in the natural image which is an efficient method due to the capability to acquire the

signal energies in few transforms value. Approximately, it expresses a multi-wavelet transforms produces countless small coefficient and few enormous coefficient. Basic de-noising techniques which utilized the multi-wavelet transforms comprise of three stage.

- Calculates the denoising image using multi-wavelet transforms.
- Based on the rules, the multi-wavelet coefficient is modified.
- This modified coefficient is used to estimates the inverse transforms

Most notable standards for the subsequent stage is thresholding. Because of its viability and where $P(i,j)$ have normal distributions $M(0,1)$. The issue is to appraise the ideal signal precisely as conceivable as per a few models. In the multi-wavelets domains, if a symmetrical multi-wavelets transforms are utilized, the issue has been defined as

$$R(i,j) = S(i,j) + M(i,j) \dots\dots(1)$$

where $S(i,j)$ denotes true coefficients, $R(i,j)$ denotes multi-wavelet coefficients of noisy image and $M(i,j)$ independents Gaussian noises. In this paper, it is proposed to research the appropriateness of various multi-wavelets base and various neighborhoods sizes, performances of mammographic sample denoising algorithm based on the PSNR.

2. Materials and Methods

Discrete Multi Wavlet Transform

The Discrete Multi-Wavelet Transforms (DWT) of images signal creates the non-redundants image representations that provide superior spectral and spatial image formations and localizations, comparing to various multi-scale representation like as Laplacian and Gaussian pyramids. Nowadays, the denoising of mammographic images uses Discrete multi-wavelet Transforms which have more attraction in this fields. The DWT has been deciphered as decomposition of signals in independents sets, spatial orientation of frequencies channel. The signal S is gone over the two corresponding channels and rises as two signal, approximates and detail. This is defined as analysis or decompositions [27]. The parts can be collected go into the first signals without data loss. This procedure is defined as synthesis or reconstructions.

The mathematical expression, which suggests examination and synthesis, denoted as discrete multi-wavelet transforms and their corresponding inverse transformations. The images may decomposing into a succession of various spatial resolutions image utilizing DWT. In the event of 2D images, a N levels of decompositions are implemented results about $3N+1$ diverse frequencies band specifically, LL, LH, HL and HH as appeared in figure 1. This is likewise recognized by different name, the sub-bands might be distinctly h^1 defined horizontal fluctuations, a^1 defined primary average image, d^1 defined the primary diagonal fluctuations and v^1 defined vertical fluctuations. The sub-images a^1 is designed by estimating the patterns along row of the images monitored by processing patterns along its column.

The similar way, changes are likewise made by generated patterns along row followed through patterns along column. The following multi-wavelet transforms levels are apply on lower frequencies sub-band images LL. Gaussian noises are averaging in lower frequencies multi-wavelet coefficient. Consequently, just the multi-wavelet coefficient in the higher frequencies level should be thresholds.

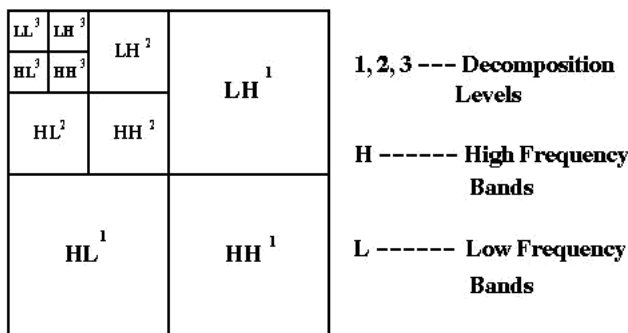


Fig 1. Decomposed Wavelet Transform

Multi Wavelet Based Image Denoising

Almost many of digital image has some noise levels. Image denoising techniques are implemented to remove these noises from images. In a perfect world, there will be no noise or additional artifact in the resulting denoised images. The Gaussian-Multi Wavelet technique is utilized to denoise the Gaussian noise present in the mammogram image which is an efficient method due to the capability to acquire the signal energies in few transform values [28].

In the image denoising process, the threshold has significant roles and estimating the optimal thresholds is difficult. The smaller threshold values will hold the noisy coefficient while a larger threshold value prompts the loss of coefficient which conveys image signals detail. Generally, soft thresholds and hard thresholds methods are utilized for such denoising process. Hard thresholding is a keep or murder rule though delicate thresholding recoils the coefficients over the edge in outright worth. It is a therapist or murder rule. Hard threshold is a retention or kill rule, though a soft threshold is a summary or kill rule that summarizes the coefficient in the threshold.

Improved K-Svd Denoising Algorithm

K-SVD methods are based upon inadequate representation [28], presently the short survey the principle numerical concepts of the K-SVD denoising methods. Assume $g, f \in \mathbb{R}^{S1 \times S2}$ be the $S1 \times S2$ noise image size and clear image, correspondingly [29]. In order to simplify the notation, here consistently utilize the lowercase alphabet, for example, $g \in \mathbb{R}^{S1 \times S2}$ to denote a column vector, and the maximum a-posteriori probability g . As per the most maximum a-posteriori probability (MAP) estimators and a supposition that every smaller images fix may be inadequately represents as a linear combinations of a redundant learning dictionaries.

The K-SVD algorithm can be explained in the following steps; (1) selecting atom from input images; (2) Atom is patched from input data; (3) Patches are overlapped; (4) Replacement of unused atoms with minimum signals; (5) Identifies the signal which utilized k-th atoms (non-zero records in row of X); (6) Deselects the k-th atoms in dictionary; (7) Estimates the error matrix code for the signal; (8) Using the RANK-1 approximations SVD, the eliminate the error matrix. All the above steps are repeats when way to the entire image is inadequately marked

Hard Threshold For Multi-Multi Wavelet

This techniques describes, how to evaluate coefficient of multi-wavelet Thresholds in Image Denoise. In spite of the fact that the techniques for hard and soft thresholds are broadly almost, there are numerous issues their natures [29]. At the point when hard thresholds are keeps datum more prominent than thresholds, and each information's not exactly the thresholds values become zero, the equations are given below:

$$A'_{j,k} = \begin{cases} A_{j,k} & \dots \dots \dots |A_{j,k}| \geq \sigma \\ 0 & \dots \dots \dots |A_{j,k}| < \sigma \end{cases}$$

In which s denotes thresholds and $A_{j,k}$ denotes the multi-wavelet coefficient [29]. At the point when hard thresholds, $A_{j,k}$ is irregular at s may brought few concussion and enormous mean-square deviations to the reconstruction of signals.

Denoising Process For Multi- Wavlet

The noisy images can be expressed below:

$$I(i,j) = X(i,j) + n(i,j) \quad i,j=1,2,\dots,N$$

Where $n(i, j)$ denotes white Gaussian noises , its mean values become zero, s denotes variances, and $X(i,j)$ denotes original signals. The issue of denoising is the manner by which to recovers $X(i, j)$ from $I(i, j)$. Equation (12) is gotten when formulae (11) are applies with multi-wavlets.

$$W_i(i,j) = W_x(i,j) + W_n(i,j)$$

Multi-wavelets transforms of Gaussian noises are also known as Gaussian distributed [1]. These elements of various sizes, yet vitality appropriates equitably in higher frequencies locations, and the particular image signals has anticipating area in each higher frequencies component. So denoising images will be operated in higher frequencies locations of multi-wavelet transforms.

Novel Thresholds

VisuShrink

VisuShrink is the type of thresholding which is applied Universal thresholds implemented by Donoho and Johnstone. The expression for this threshold is defined as $\sigma \sqrt{2 \log M}$ where σ denotes variances of noise and M denotes image pixel counts. It is demonstrated that limit of whichever M value iid as $N(0, \sigma^2)$ can smaller than universals thresholds with higher probabilities, with the likelihood moving toward 1 as M increments. Along these lines, with higher likelihood, an unadulterated commotion signals are evaluated as indistinguishably zero.

Bayesshrink

Adaptive data-driven thresholds are the type of threshold that is called as BayesShrink. This threshold is especially utilized for denoising images through Multi-Wallet soft-thresholding techniques. The thresholds are operated in a Bayesian frameworks and is considered to be a generalized Gaussian distributions (GGT) for multiple wavelet coefficient in every details sub-band and reduces Bayesian risk by attempting to find threshold T .

Neighshrink

Each noisy multi-wavelet coefficients must be compressed by $W_{i,j}$, which has a square neighborings windows centered on B_{ij} . $L \times L$ denotes the windows sizes of neighborhood, where L denotes the positive odd numbers. In each and every sub-bands, the various Multi-wavelet coefficients sub-band is independently compressed, however windows sizes neighborhood, thresholds λ and L remains unchanged. When $S_{i^2, j}$ summations has pixels index out of the Multi Wavelet sub-band run, the comparing term in the summations is excluded. The inadequacy of this technique is that utilizing a similar universal thresholds λ and windows sizes of neighborhood L in each sub-band remains suboptimal.

SureShrink

SureShrink is a types of thresholding wherein adaptive thresholds are apply on each sub-bands, a different thresholds are estimates for every details sub-band dependent on SURE (Stein’s unbiased estimators for risks), a technique for evaluating the losses in the unbiased condition. The optimum values of λ and L of each sub-bands ought to be information independent and reduces mean squared error (MSE) or risk factors of relative sub-bands. Providentially, Stein have expressed that MSE is assessed unbiased from observed informations. Using SURE, optimize the NeighShrink, for each multi-wavelets sub-bands, the optimal thresholds and windows sizes of neighbors can be arranged in a 1-D vectors for the subband's noisy multi-wavelets coefficient. For ease of notations, the Noisy Multi Wavelet coefficients from subband 's' can be arranged into the 1-D vector. Also, we combines the N_s obscure quiet coefficient from sub-band 's' into the comparing 1-D vectors.

3. Results and Discussions

For the multi-wavelets and new thresholds techniques are described above, image denoising are performing through multiple wavelet from second to fourth levels decompositions, and responses are displayed in Figures and Tables for secondary noise decompositions for various noise variation. This is discovered that three levels decompositions and fourth levels decompositions caused more blur. The investigations were finished utilizing a windows sizes of 3X3, 5X5 and 7X7 for nwe Multi-Wavelet thresholding Strategy. The local window of 3X3 and 5X5 are acceptable decisions for mammographic image. The mammographic images are obtained from the MIAS databases.

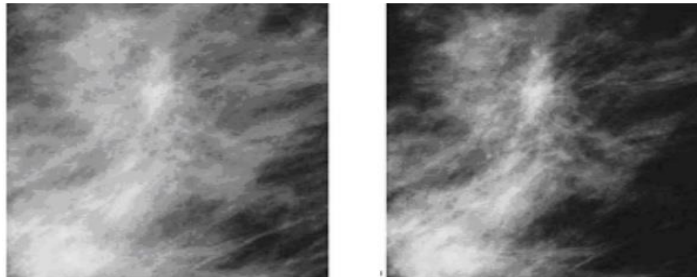


Fig 2 Original Noise Brest Cancer Mammogram Images

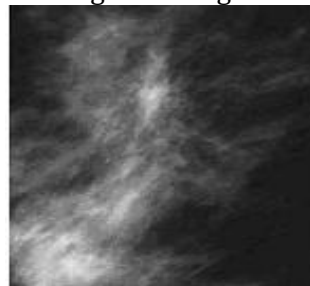
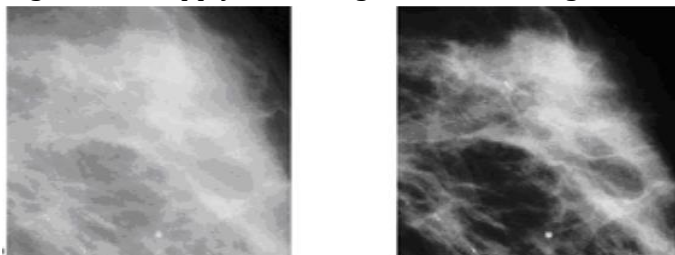


Fig.3 After Apply K-VSD Algorithm Mammogram Image



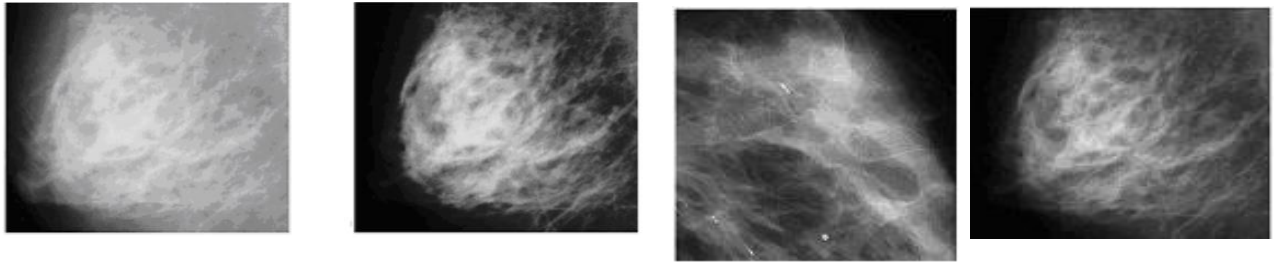


Fig4 After Applied Multi Wavelet Novel Threshold Method (Denoised Mammogram Images)

| Window Size | | 3X3 | | | | 5X5 | | | | 7X7 | | | |
|--------------|----------------------------|----------|---------|---------|---------|---------|---------|---------|--------|---------|--------|--------|---------|
| | | Variance | 0.02 | 0.04 | 0.06 | 0.08 | 0.02 | 0.04 | 0.06 | 0.08 | 0.02 | 0.04 | 0.06 |
| Multi Wavlet | Noisy Image | 16.86 | 14.1096 | 12.64 | 11.6742 | 16.830 | 14.0995 | 12.671 | 11.681 | 16.846 | 14.103 | 12.64 | 11.6592 |
| | Wiener | 24.05 | 21.343 | 19.9475 | 19.022 | 26.4167 | 24.146 | 22.8984 | 21.98 | 26.6335 | 24.826 | 23.732 | 22.909 |
| Harr | Visushrink | 22.29 | 19.7787 | 18.37 | 17.3849 | 22.273 | 19.7681 | 18.376 | 17.431 | 22.285 | 19.807 | 18.33 | 17.4044 |
| | Neighshrink | 24.5738 | 23.306 | 22.2924 | 21.543 | 24.5822 | 23.245 | 22.3749 | 21.55 | 24.5573 | 23.254 | 22.287 | 21.571 |
| | Mod. Nei | 25.96 | 25.0158 | 24.1295 | 23.4049 | 25.962 | 24.9922 | 24.203 | 23.438 | 25.957 | 24.988 | 24.09 | 23.3887 |
| | Proposed K – VSD Multi Wav | 27.87 | 27.044 | 26.2441 | 25.966 | 28.189 | 27.733 | 27.1236 | 25.11 | 28.3468 | 27.877 | 26.879 | 26.001 |
| | Visushrink | 22.62 | 20.0023 | 18.45 | 17.5362 | 22.617 | 19.9746 | 18.470 | 17.506 | 22.614 | 19.97 | 18.50 | 17.5385 |

| | | | | | | | | | | | | | |
|--------|------------------------------|---------|---------|---------|---------|---------|---------|---------|--------|---------|--------|--------|---------|
| db 16 | Neighshrirk | 23.3646 | 22.3845 | 21.5909 | 21.0162 | 23.3556 | 22.4143 | 21.6199 | 21.04 | 23.366 | 22.359 | 21.629 | 21.0237 |
| | Mod. Nei | 24.332 | 23.7027 | 23.0889 | 22.5978 | 24.3175 | 23.7657 | 23.1492 | 22.627 | 24.3335 | 23.681 | 23.129 | 22.5932 |
| | Proposed K – VSD Multi Wav | 26.412 | 25.9421 | 25.6012 | 25.015 | 26.4561 | 25.9455 | 25.4588 | 25.104 | 26.4563 | 25.978 | 26.459 | 24.894 |
| Sym 8 | Visushrink | 22.6042 | 19.9785 | 18.5036 | 17.4728 | 22.5682 | 19.9576 | 18.5172 | 17.517 | 22.6058 | 19.984 | 18.454 | 17.4988 |
| | Neighshrirk | 23.4209 | 22.5088 | 21.6579 | 21.1155 | 23.464 | 22.4881 | 21.7373 | 21.053 | 23.4157 | 22.482 | 21.628 | 21.0469 |
| | Mod. Nei | 24.388 | 23.8718 | 23.2045 | 22.7326 | 24.4283 | 23.8263 | 23.2761 | 22.688 | 24.3611 | 23.833 | 23.159 | 22.6622 |
| | Proposed K-VSD Multi Wavelet | 26.1334 | 26.146 | 26.4782 | 24.9462 | 26.4165 | 25.945 | 25.9687 | 26.136 | 26.2661 | 25.978 | 25.568 | 24.9876 |
| Coif 5 | Visushrink | 22.5678 | 19.9391 | 18.5022 | 17.5062 | 22.6137 | 19.9899 | 18.4535 | 17.497 | 22.6153 | 19.917 | 18.486 | 17.4952 |
| | Neighshrirk | 26.0778 | 24.2732 | 23.1822 | 22.2243 | 26.0365 | 24.3298 | 23.0888 | 22.289 | 26.0615 | 24.278 | 23.123 | 22.2693 |
| | Mod. Nei | 27.2788 | 26.008 | 25.0155 | 24.1331 | 27.2752 | 26.0147 | 24.9283 | 24.161 | 27.2978 | 25.981 | 24.999 | 24.1564 |

| | | | | | | | | | | | | | |
|------------------------------|---------|--------|---------|---------|---------|---------|---------|--------|---------|---------|---------|--------|--|
| | | | | | | | | | | | | | |
| Proposed K-VSD Multi Wavelet | 32.3458 | 29.455 | 29.3464 | 28.5781 | 28.3756 | 30.4655 | 30.1005 | 29.489 | 29.3201 | 29.0172 | 29.0756 | 29.453 | |

Table I
Comparative Mammographic image PSNR Values for Proposed (K-VSD) with Novel Threshold Multi Wavelet and Other Existing Methods

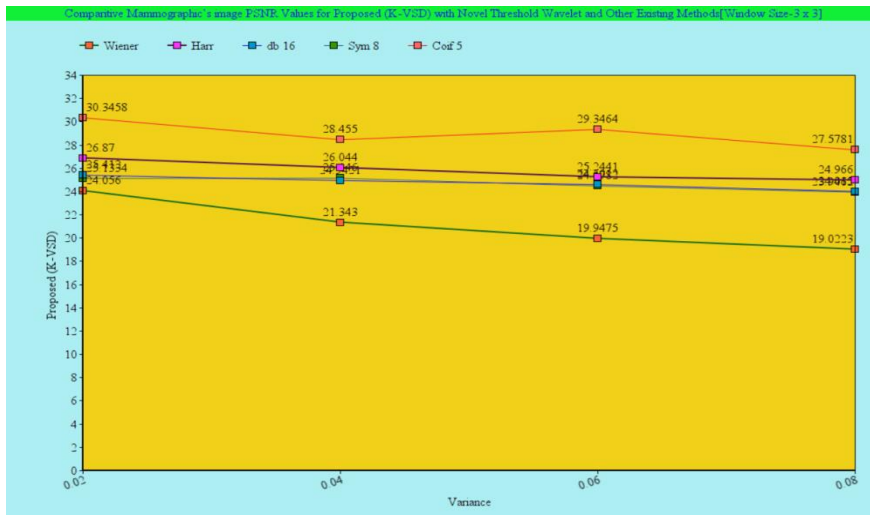


Fig 5 Comparative Mammogram Image PSNR Values for Proposed (K-VSD)-Window Size:3 x 3

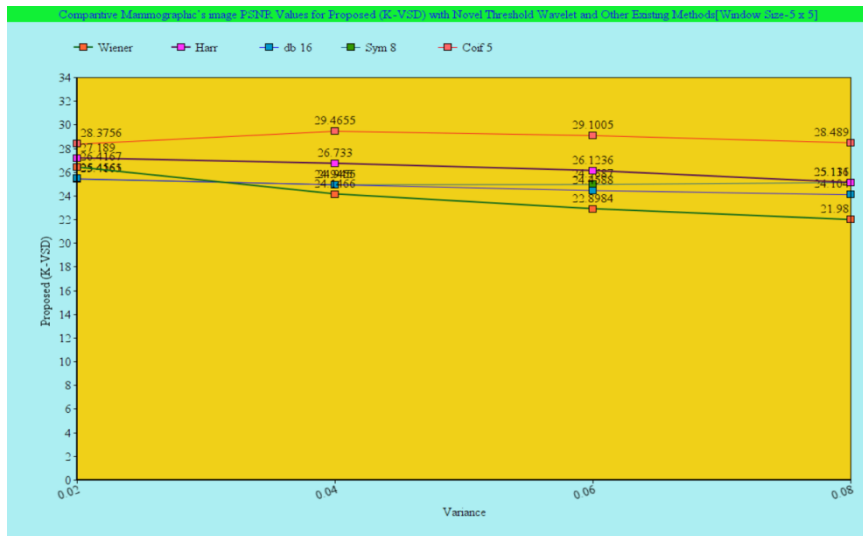


Fig 6 Comparative Mammographic's image PSNR Values for Proposed (K-VSD)-Window Size:5 x 5

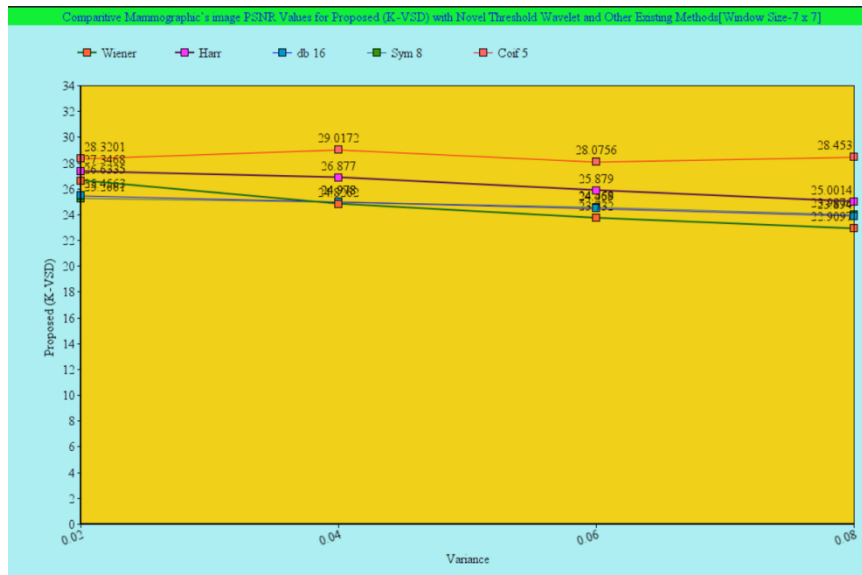


Fig 7. Comparative Mammographic's image PSNR Values for Proposed (K-VSD)-Window Size:7 x 7

Evaluation Criteria For Multi Wavlet Threshold Method

The proposed method is analyzed by the objective quality measures Peak Signal to Noise ratio that is estimated by the following equations,

$$PSNR = 10\log_{10} \frac{255^2}{MSE} \text{ (db)}$$

in which, MSE denotes mean squared error between reconstructed de-noised images and original images, which is utilized to assess the distinctive denoising methods, such as the Visushrink, Wiener filter, Neighshrink, Multi Wavelet and Modified Neighshrink for each mammographics image.

4. Conclusion

In this paper, improving the visual quality of mammograms using image processing is an significant research challenges for early stages breast cancer detections. This article depicts novel strategies for predicting the mammographic image of noise suppressions depends upon multi-wavelet transforms. Pre-processing of the image is modeled to enhancing local contrast in dense surroundings. The image denoising methods are adaptive and selecting a gain factors provide the desire and comprehensive improvement. Initial methods indicates that our techniques improve detections of microcalcification and other suspicious structure, level in difficult situation (for example in lower contrasts images regions, in dense tissue), and experiments have been conduct to investigate the appropriateness of various multi-wavelets with new thresholds at various windows size. The experimental result demonstrated that new threshold Neighsureshrink was superior to the multi-wavelet domains coefficients comparing with the Neighshrink, Visushrink, Wiener filter and modified Neighshrink. The proposed technique require minimal users adjustments parameter. At long last, our proposed Novel thresholding technique has created excellent mammographic's screening result for physician for the early recognition of breast cancer, and the proposed techniques has produced better PSNR value.

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