Mask-Nha Based Image Denoising with Random Walker Segmentation

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ABSTRACT--- The search for well-organized image de-noising techniques is still a valid challenge at the crossing of functional learning and statistics. In spite of the refinement of the currently proposed methods, most algorithms have not yet succeeded a desirable level of applicability. In order to reduce the drawbacks in the earlier methods, a novel algorithm probabilistic method is associated as two-dimensional non-harmonic analysis called mask non-harmonic analysis such a way that the noise is degraded in the input image. In this, the entire region of the image is considered as homogeneous texture. But when the noise content is more, the segmentation of a noisy image into original images become more complex. Hence, Random walker segmentation is implemented for segmentation with canny detection algorithm in order to preserve edges. Then the regions obtained from the segmentation are analyzed using mask NHA algorithm. Theoretical analysis and experimental results are reported to illustrate the usefulness and potential applicability of our algorithm on various computer vision fields, including image enhancement, edge detection, image decomposition, and other applications.

Index terms: Image de-noising, 2D-NHA, Segmentation, Random Walker, Canny edge detection, Mask NHA

1. INTRODUCTION

A large number of Digital Images across the internet has given rise to more systemize and effective image restoration methods. Noise is forcibly added into the system and may cause severe damage to images. This presence of noise in the image results to reduce outputs in various applications such as photography and segmentation [1], HDR imaging [2], and recognition [3], etc. Image de-noising aims to recover the clean image x from its noisy observation y = x + n, where n is the corrupted noise. This problem has been extensively studied in the literature, and numerous statistical image modeling and learning methods have been proposed in the past decades [4, 5].In this paper, we assume that the noise is additive white Gaussian noise (AWGN) and the noise level is given. In order to handle practical image de-noising problems, a flexible image de-noise is expected to have the following desirable properties: (i) it is able to perform de-noising using a single model; (ii) it is efficient, effective and user-friendly; and (iii) it can handle spatially variant noise. Such a de-noise can be directly deployed to recover the clean image when the noise level is known or can be well estimated. When the noise level is unknown or is difficult to estimate, the de-noise should allow the user to adaptively control the trade-off between noise reduction and detail preservation. Furthermore, the noise can be spatially variant and the de-noise should be flexible enough to handle spatially variant noise [6].

However, state-of-the-art image de-noising methods are still limited in flexibility or efficiency. In general, image de-noising methods can be grouped into two major categories, model-based methods and discriminative learning based ones. Model-based methods such as BM3D [7] and LRF [8] are flexible in handling de-noising problems with various noise levels, but they suffer from several drawbacks. For example, their optimization algorithms are generally time-consuming, and cannot be directly used to remove spatially variant noise.

Image segmentation has frequently been defined as the problem of localized regions of an image relative to content (e.G., image homogeneity). However, new image segmentation techniques have furnished interactive strategies that implicitly define the segmentation problem relative to a specific idea of content localization. The technique described above requires a person or any processor to control or monitor the segmentation of ROI from the image. Practical interactive segmentation algorithms have to offer four qualities: 1) Fast computation, 2) Fast editing, 3) A capability to produce an arbitrary segmentation with sufficient interaction, four) Intuitive segmentations. The random walker algorithm delivered right here exhibits all of those favored features. The random walker algorithm requires the solution of a sparse, symmetric positive-definite system of linear equations which may be solved quickly through a variety of methods. The algorithm may perform fast editing by using the previous solution as the initialization of an iterative matrix solver [9].

We provide an intensive evaluation between our method and three other algorithms on images. Finally, we can justify that our algorithm can outperform valid results when compared to state of art methods in de-noising of an image. Our algorithm achieves advanced de-noising effects at the same time as maintaining greater detail. We show applications of our algorithm on real-world images from the domains of well-known images, clinical imaging, high-resolution virtual images, and astronomy, and discussion potential extensions to our framework

2. LITERATURE SURVEY

Yoshizawa, T., et al. [11] implemented a frequency analysis based on high resolution in order to overcome the noise in the periodic signals.

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Considering the time domain the variations are low, here method is considered in order to eliminate the variations that occur in the frequency domain. In this method, a non-harmonic analysis was used in which the frequency resolution is high and along with the frame length in order to reduce the noise. Here, investigations reveal that the NHA algorithm provides better results but the computational complexity is high.

Leo Grady [9] implemented a new method for image segmentation through a multi-level and interactive segmentation. The user-defined labels are assigned and determined in order to estimate the probability such a way that the random walker should be started at a pixel which is prelabelled. Meanwhile this the greatest probability is selected to the prelabelled pixels, high-quality image segmentation may be obtained but this process is low.

Hasegawa, M., et al. [13] implemented a technique in order to reduce the problems in the image reconstruction by estimating the signal based on the non-harmonic interpretation. This method was implemented for extracting the specific spectra, without depending on the function of the window and the resolution of a frequency of this method is also minor than that of the discrete Fourier transform. Based on the spectrum obtained from the NHA method the new textures of the image were generated. During the extraction of these new features, some of the regions were missed and these are repaired using the modified cost function for two-dimensional non-harmonic analysis. But this method also computationally high complex procedure.

A. K. Sinop and L. Grady [10] presented a basic structure for seeded image segmentation algorithms that allows two of the best methods as special cases - The Graph Cuts and the Random Walker algorithms. The formulation of this common framework normally suggests a new, third, algorithm that we develop here. Specifically, the former algorithms may be determined to minimize certain energy with respect to either an l1 or an l2 norm. Here, the segmentation algorithm defined by an l_∞ norm, provide a method for the optimization and show that the resulting algorithm produces an accurate segmentation.

Chunhua Dong et.al [12] produced a prior knowledge on the method of segmentation using the random walker framework on the volumetric pathological image. The main process involved in this procedure is to use the earlier segmented image slice to obtain the shape and intensity values of the present segmented slice. Based on the previous knowledge the foreground and background region can be dynamically updated for the present slide by fusing the narrowband threshold method and device model with a Gaussian process. The output image with increasing quality is achieved using Bayes RW algorithm.

Marc Lebrun [14] implemented an algorithm based on block matching 3d filtering which is a novel noise removal algorithm based on the sparse representation of the transform domain. In this procedure, the images are grouped into the 3-dimensional groups. Though this procedure provides valid results it has several drawbacks. Some of the drawbacks are complexity, limited flexibility and slower than other techniques. This method also provides poor results for skin regions.

Fei Xu., et al. [15] implemented de-noising techniques based on the low-rank matrix factorization in which PCA is also performed for dimensionality compression. This is executed using the low-rank matrix factorization element. This method requires only the upper bound of the low-rank matrix besides the precise value. This method provides various advantages in removing the noise when compared to state of art methods.

Ma, H., & Nie, Y. [16] proposed enhanced anisotropic diffusion models for image de-noising. The proposed model was utilized for classifying the different data of images like smooth regions, edges, corners and isolated noises by using the specific parameters and gradient variation parameter. Furthermore, an edge fusion method was proposed for edge-preserving after de-noising by fusing the several de-noising and edge detection methods. Originally, the de-noised images were acquired by using de-noising methods and then the edge images of de-noised images were captured by edge detection methods. After that, the selected edge images were fused with more edges for restoring the edges of de-noised images.

3. PROPOSED METHODOLOGY

In this area, a novel technique for image denoising and segmentation is proposed by combining the Mask NHA and random walker algorithm. While using the discrete Fourier and discrete cosine transform provides side lobes and the period of the signal is not an integer value. Therefore, it is not an easy procedure to split the sidelobes and noise for the amplitude of these transforms. For complete portioning of sidelobes a method named as threshold denoising is implemented. This method provides valid results in solving the side lobe suppression problem. This thresholding is done based on the NHA analysis. In the proposed system the random walker segmentation is developed along with the NHA artifacts. The proposed algorithm is explained below:

3.1. 2D NHA

Generally, Mask non harmonic analysis is represented in two dimensional spatial domain in 2D discrete transform as follows:

$$\boldsymbol{Y(k,l)=\sum_{k=0}^{N-1}\sum_{l=0}^{M-1}I(m_1-m_2)e^{-j2\pi(\frac{km_1}{N}+\frac{lm_2}{M})}} \quad (1)$$

In equation (1), the image signal is referred as I, and their sizes are indicated as M and N. Hence the entire window size is given as M×N and assumed by the short Fourier transform. The frequency resolution of DFT is limited by the integer period of $\frac{K}{N}$. If this period is not an integer value the extra side lobes are appeared. Sinusoidal wave fitting [13] is used for estimation of Fourier coefficients and this can be expressed as follows:

$$\boldsymbol{I(m_1,m_2)=\hat{A}cos(2\pi\frac{\hat{f}x}{fx_s}m_1+\frac{\hat{f}y}{fy_s}m_2+\widehat{\emptyset})} \quad (2)$$

In equation (2), $\hat{A}$ refers the magnitude of the sinusoidal model, $\hat{f}x$ and $\hat{f}y$ are the spatial frequencies, and $\hat{\emptyset}$ is the phase parameter of the model. The sampling frequencies are signified as fx_s and fy_s again in that each of them are represented as $fx_s = \frac{1}{\delta x}$ and $fy_s = \frac{1}{\delta y}$ respectively where x and y are considered as the image representation in two dimensional. By this method the mean square error is reduced in between the input image and finally extracted noise free image. This can be obtained using the steepest descent algorithm. Then obtained quality metrics are represented using below equation:

$$S(\widehat{A}, \widehat{f_x}, \widehat{f_y}, \widehat{\emptyset}) = \frac{1}{M_1 M_2} \sum_{m_1=0}^{M_1-1} \sum_{m_2=0}^{M_2-1} \{I(m_1, m_2) - \hat{I}(m_1, m_2)\}^2 \quad (3)$$

The equation (3) is solved by calculating the 2D dct coefficients as the first values. But the resolution of the image by considering the dct coefficients is depend on the size of the window. But if we eliminate the side lobes the information of the original data may be loss. Hence, using our proposed method we suppress the sidelobes instead of eliminating them and in turn the frequency resolution also increases.

3.2. Mask NHA

A patch is considered in the unit size and it is used for denoising the image by transferring the image from one domain to another. The smoothing and denoising of the image is based on the dimensions of the patch. The edge is converted into the sinc function by utilizing the DFT. By considering the threshold for noise removal it may reduce the sinc function which results to deduction in the edges of the image. If we restored the image from the above process the image may be obtained with ringing artifacts. The edge data of the image is also vanished due to suppression of the side lobes. A window is required for masking operation in a way to minimize the non stationarity in the signal. This mask can be obtained based on the segmentation results.

The segmentation process is done by separating the image filled with noise into two regions such as edge region and texture region. Again the texture region which contains the texture features of the image is divided into more other regions by grouping the regions with similar features. Hence, the target region is denoted as Ω, and the remaining region is denoted as $\widehat{\Omega}$. The weighting factor $w(m_1, m_2)$ is determined by considering the binary information from these two regions Ω and $\widehat{\Omega}$. The generated weighting factor is called as the masking matrix. If the outer region is represented in the image then the weighting factor is 1 and if it is the target region then the weighting factor is represented with 1. The cost function is given as follows,

$$S(\widehat{A}, \widehat{f_x}, \widehat{f_y}, \widehat{\emptyset}) = \frac{1}{M_1 M_2} \sum_{m_1=0}^{M_1-1} \sum_{m_2=0}^{M_2-1} w(m_1, m_2) \times \{I(m_1, m_2) - \hat{I}(m_1, m_2)\}^2 \quad (4)$$

The cost function is used for extracting the spectrum from Ω excluding $\widehat{\Omega}$. While the primary values are assigned by the Fast Fourier Transform (FFT), Ω must be given the temporary value.

3.3. Random Walker Segmentation

Segmentation of the image refers to the dividing the regions of the image into various groups based on their features and removing all the unnecessary regions. The main applications on image processing such as pattern recognition and low-level computer vision are based on the image segmentation. Particularly in image vision applications the feature extraction, feature description and image understanding like middle level and low level technique are implemented based on the segmentation techniques. Since this method leads to various applications it has some problems in perfect dividing the image into groups.

Hence the random walker algorithm [9] solves the above stated problem by representing the image on the graph and each and every node can be denoted with pixel or voxel value. Then using the RW algorithm the probability of each pixel is considered by estimating the graph of the pixel values. A walker moves on the graph and first reaches the seeds on the foreground then reaches the background seed. This process can be continued after finding the probabilities of the pixels using the linear system of equations with Laplacian matrix. This matrix equation can be expressed as follows:

$$A_{ij} = \begin{cases} d_i \; i = j \\ -w_{ij} \; v_i \text{ and } v_j \text{ are adjacent nodes} \\ 0 \text{ otherwise} \end{cases} \quad (5)$$

Where A_{ij} is indexed by vertices v_i and v_j. $w_{ij} = \exp\left(-\beta(I_i - I_j)^2\right)$, is the edge weight, and I_i, I_j indicate the image intensity at vertices v_i and v_j, respectively. β represents a tuning constant that depends on the user.

Given a weighted graph, a set of marked (labeled) nodes, V_M, and a set of unmarked nodes, V_U, such that $V_M \cup V_U = V$ and $V_M \cap V_U = \emptyset$, we would like to label each node $v_i \in V_U$ with a label s. $s = 1$ stands for the foreground, and $s = 2$ stands for the background. Assuming that each node $v_j \in V_M$ has also been assigned with a label s, we can compute the probabilities, x_i^s , that a random walker leaving node v_i arrives at a marked node v_j by solving the minimization of

$$Y_{int}^s = \frac{1}{2} x^{sT} L x^s \quad (6)$$

All nodes V are divided into two sets: the marked (pre-labeled) nodes V_M and unlabeled (i.e., free) nodes V_U. Therefore, the above function can be reformulated as follows:

$$Y_{int}^s = \frac{1}{2} \left[x_M^{sT} x_U^{sT} \right] \begin{bmatrix} L_M & B \\ B^T & L_U \end{bmatrix} \begin{bmatrix} x_M^s \\ x_U^s \end{bmatrix} \quad (7)$$

Minimization of (7) with respect to x_U^s the random walker problem can be solved by the following system of equations:

$$A_U x_U^s = -B^T x_M^s \quad (8)$$

The variable x_U^s represents the set of probabilities corresponding to unmarked nodes; x_M^s is the set of probabilities corresponding to marked nodes (i.e., “1” for foreground nodes and “0” for background nodes). By virtue of x_i being a probability,

$$\sum_{s=1}^{2} x_i^s = 1, \ \forall l \quad (9)$$

4. RESULTS AND DISCUSSIONS

For segmentation, the results are checked and verified with the mean shift algorithm for both the mask NHA and random walker segmentation of mask NHA and random walker segmentation. LIVE database images were taken for verifying the results.

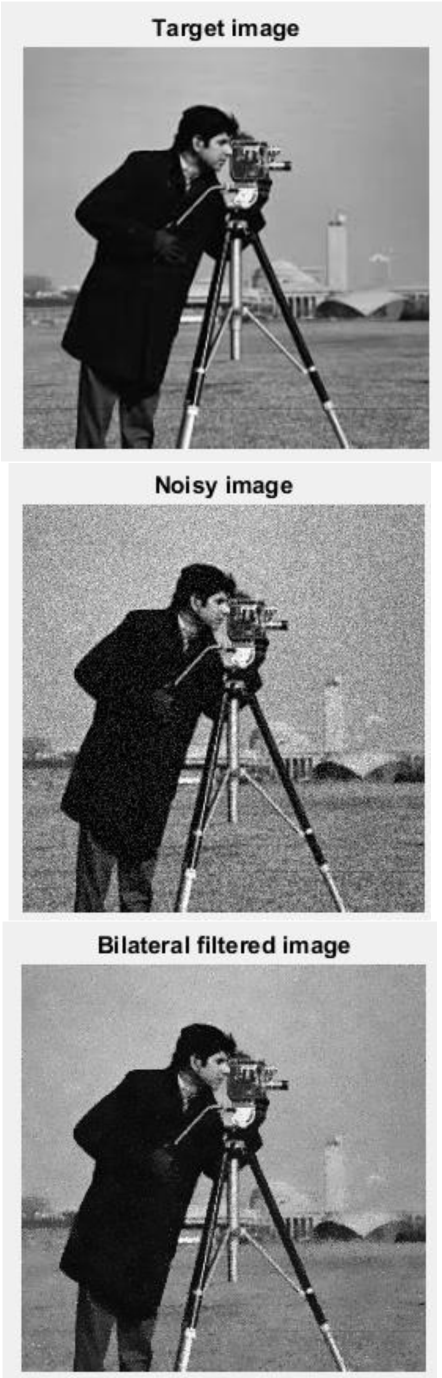

Figure 1(a). Target image Figure 1(b). Noisy image Figure 1(c). Bilateral filtered image

The target image cameraman, noisy image containing additive white Gaussian noise were shown in figure 1(a) and figure(b) respectively. Depending upon the input image features,. The parameters required for cameraman image is taken depending upon the input image features . Accept thresholding process, the parameters are taken as constant throughout the procedure. The pre processing step is done using the bilateral filter for the noisy image. Fig 1(c) shows the output of the preprocessing step is done by using the bilateral filter. This filter is a non-linear method. The output of the image may be blurred with preserved edges is occurred in order to smooth the image.

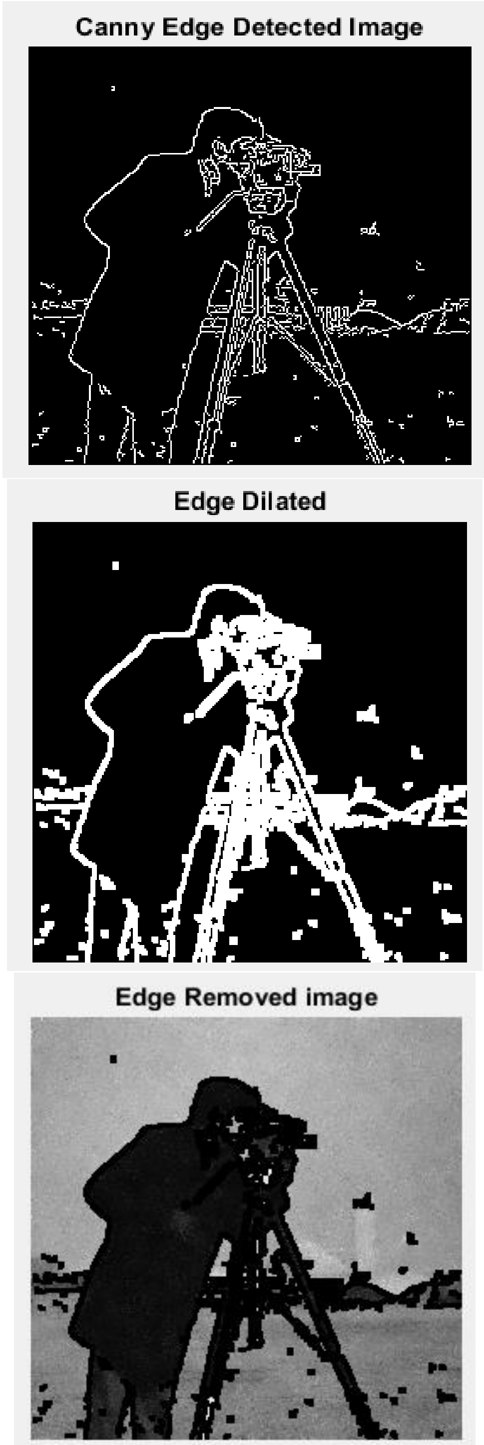

Figure 2 (a). Edge detected image Figure 2(b). Edge dilated image Figure 2 (c). Edge removed image

Figure 2(a) represents the edge detection image which is implemented by using the canny edge detection method. To improve the qualities of the canny edge by using bilateral filtering. Figure 2(b) represents the output edge dilation which is implemented to define the region of edges. Figure 2(c) represents the edge removed image. This task was performed by a mask is to be considered and it is applied as window on the input image. The area obtained from the masking is used further in image segmentation process.

Figure 3(a): Random walker Figure 3(b): Texture boundary Figure 3(c): Denoised image using segmentation Segmentation Mask-NHA

Image segmentation is one of the most important bottleneck technologies and important image processing issue for pattern recognition and low level computer version. The process of dividing the image into meaningful parts and deleting the unwanted data is known as segmentation,.. Figure 3(a) represents the Random walker segmentation is obtained through a graph model based on a fixed number of vertices and edges .Figure 3(b) represents texture boundary segmentation. The texture boundaries are defined by reducing the boundary distortion.

Image denoising using domain transformation often employs a block unit called a “patch.” Which are extracted from the layers of interest. When the patch size increases the smoothing effectiveness of denoising increases. Spectra is calculated by using Mask-NHA. Figure3(c) represents the denoised image using Mask-NHA that can be obtained by the process of thresholding which cane be restored by combining all the layers .

Sigma values	PSNR(dB)		MAE		SSIM	
	Mask-NHA with mean-shift	Mask-NHA with Random walker	Mask-NHA with mean-shift	Mask-NHA with Random walker	Mask-NHA with mean-shift	Mask-NHA with Random walker
σ= 5	42.0226	46.5807	1.6033	.4361	0.9702	0.9944
σ= 10	41.9099	46.2333	1.6574	.4724	0.9702	0.9936
σ= 15	40.3452	45.7369	1.7811	0.5296	0.9697	0.9921
σ= 20	39.8281	45.6390	1.9231	0.5417	0.9698	0.9920
σ= 25	39.3706	45.0310	2.0517	0.6231	0.9695	0.9898
σ= 30	38.8172	44.8217	2.1923	0.8412	0.9688	0.9873

Table 1: Comparison of mean shift Mask-NHA and Mask-NHA with Random walker method for cameramen.

Table 1: represents the comparison in terms of PSNR,MAE and SSIM which are calculated at different noise intensity values for the proposed Mask-NHA denoising method with random walker segmentation and the MASK-NHA denoising method. In terms of PSNR the proposed method is effective with the comparison of mean shift segmentation between σ = 5 and σ = 30 .In terms of MAE, the proposed method is robust in between σ = 5 and σ = 30. The objective evaluation indicator as SSIM and found that proposed method out performs than the other method. The proposed method is better than other methods was prove by the experimental results. The proposed method produces flawless results applied on different images for diverse applications are compared to all other techniques of image denoising Image segmentation and random walker segmentation t can be facilated by the indication of denoising.

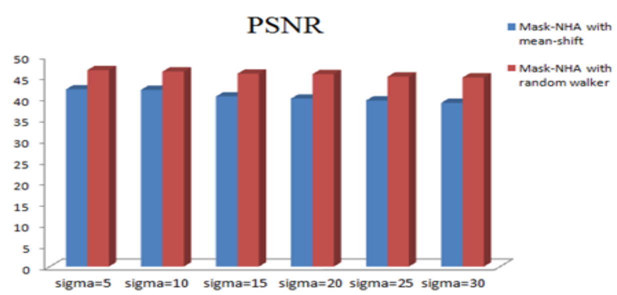

Figure 4(a): Comparison of PSNR for Mask-NHA with mean-shift and Mask-NHA with random walker segmentation

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The bar graphs of random walker segmentation for the comparison of PSNR for MASK-NHA with mean-shift and Mask-NHA .The PSNR of Mask-NHA with random walker produces better results compared to the Mask-NHA with mean-shift.

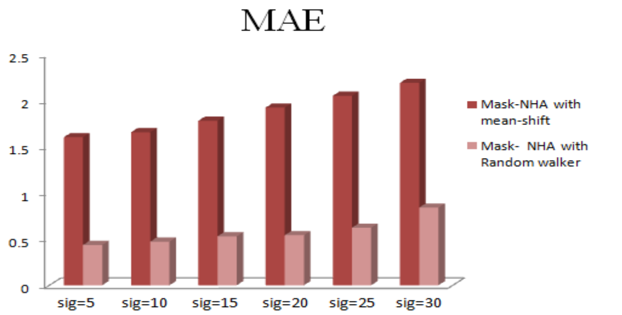

Figure 4(b): Comparison of MAE for Mask-NHA with mean-shift and Mask-NHA with random walker segmentation

The bar graphs of random walker segmentation for the comparison of PSNR for MASK-NHA with mean-shift and Mask-NHA .The MAE of Mask-NHA with random walker produces better results compared to the Mask-NHA with mean-shift.

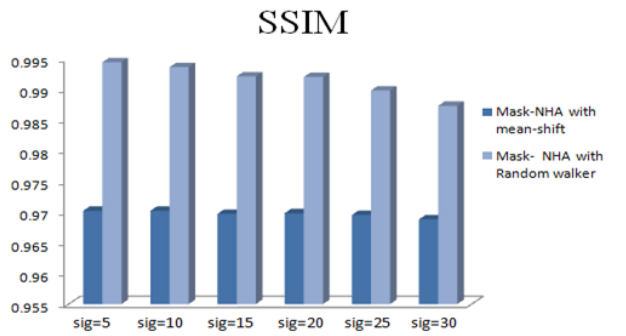

Figure 4(c): Comparison of SSIM for Mask-NHA with mean-shift and Mask-NHA with random walker segmentation

The bar graphs of random walker segmentation for the comparison of PSNR for MASK-NHA with mean-shift and Mask-NHA .The SSIM of Mask-NHA with random walker produces better results compared to the Mask-NHA with mean-shift.

5. 5. CONCLUSION

In image processing techniques, image denoising is one of the most critical method. In this paper, the proposed method for efficient image denoising technique by using high-frequency resolution analysis. In the proposed technique, a new method known as mask non harmonic analysis is implemented together with the segmentation algorithm with edge preserving approach. Through the usage of the various segmentation parameters, the edge preservation is based totally on canny edge detection and random walker segmentation. Based on the thresholding method, the edge detection in denoised mages are implemented. To differentiate the effectiveness of the proposed algorithm, the experimental results of the proposed method is compared with the state-of-art techniques. The performance metrics high PSNR ,SSIM and low MAE values proves the proposed Mask NHA denoising with Random Walker Segmentation technique gives better results when compared wth the Mask NHA denoising with Mean Shift Segmentation approach.

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