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A Parameter Optimized, Automatic Threshold Selection for Enhancing Edge Preserving Denoising and Segmentation

M. Divya[1], Dr. E. Mary Shyla[2]

Research Scholar, Department of Computer Science, Sri Ramakrishna College of Arts and Science for Women, Coimbatore, India[1]

Assistant Professor, Department of Computer Science, Sri Ramakrishna College of Arts and Science for Women, Coimbatore, India[2]

Abstract: Image denoising is the most challenging issue in the field of image processing. The main task experienced during image denoising process is to categorize the components of original image from the noisy image. Hence, efficient segmentation mechanisms are needed for categorizing the noise. In Image Denoising With Edge-Preserving and Segmentation Based on Mask Non Harmonic Analysis (ID-EPS), image denoising was done in spatial domain by preserving the edges with fuzzy boundaries. The information in edges was preserved from the input image by edge detection and segmentation with the help of fixed threshold and segmentation parameters values. But in general, Performance of denoising depends on the values of these parameters. Hence optimization of threshold and parameter values is required. In proposed Enhanced Image denoising with Edge Preserving segmentation (EID-EPS) method, performance of image denoising and segmentation result is improved by using frequency domain coefficients like Discrete Cosine Transform (DCT) which segments the similar frequency patches from the input image. Moreover, Iterative Threshold Selection method is introduced for automatically selecting the threshold value for every successive iteration. Parameter values are also optimized by using Servo Parameters Optimization Algorithm in which values of parameters are selected from the input images based on the target image. Experiments are conducted to analyze the performance of denoising with the existing system.

Keywords: Image denoising; Mask Non Harmonic Analysis; Segmentation; Frequency Domain coefficients; Optimization Algorithm.

I. INTRODUCTION

Image denoising plays the major role in image processing which removes noises while preserving the edges [1]. Various noises can be easily added to the image, when it is captured or transmitted. In order to eliminate these integrated noises from an image, different linear techniques like Weiner filtering and non linear techniques like thresholding are introduced. But most commonly used technique for image denoising is filtering. Filtering technique is a linear technique that includes anisotropic filtering, bilateral filtering, total variation method, pointwise or multipoint algorithm, local and non local methods. However, linear techniques do not preserve edges in a good manner that is edges, which are considered as discontinuities in the image, were smeared out. In Multipoint method, Discrete Fourier Transform and Discrete Cosine Transform were most popularly utilized for denoising by which more side lobes were obtained. In order to overcome the mentioned limitations, non-harmonic analysis (NHA) was introduced to improve the thresholding accuracy and denoising performance.

In Image Denoising With Edge-Preserving and Segmentation Based on Mask Non Harmonic Analysis (ID-EPS) [2], NHA was utilized as the frequency analysis method which reduces the side lobes obtained from the DFT based frequency analysis method. Image was segmented into homogeneous region. Edges were then detected as well as preserved using canny edge detection method and the regions of edges were eliminated from the input noisy image. Here, the accuracy of canny edge detection was enhanced by bilateral filtering. Then the patches of an image were segmented using mean shift based image segmentation algorithm which applies mean shift on image feature space. In general, Performance of segmentation and denoising was depends on the values of segmentation parameters as well as threshold. In this system, parameter values and threshold values were fixed, which are considered as the major consequences for degrading the result and performance of denoising. Thus, effective parameter and threshold optimization algorithms are required to select the values for every iteration.

Hence, in proposed EID-EPS technique, Iterative Threshold Selection method and Servo Parameters Optimization Algorithm are introduced for automatic

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selection of threshold and parameter values. Moreover, DCT is utilized to improve the segmentation result.

II. LITERATURE SURVEY

Rishi Jobanputra & David A. Clausi (2006) [1] presented weighted grey level co-occurrence probability (WGLCP) technique in image segmentation process. It generates texture features to classify boundaries. By weighting pixel pairs in the center of the window higher than pixel pairs at the window boundary, improved features are generated. It avoids correlation which improves performance of segmentation.
Kuo-Liang Chung et al (2008) [2] presented edge-preserving algorithm for color contrast enhancement with application to color image segmentation. Here edge preservation operation is extended along with saturation and desaturation operation of color contrast enhancement algorithms. For colour image segmentation, two phases such as seed-based region growing phase and the merging phase is employed. This method reduces computational complexity and provides efficient results in edge preservation.
Gang Dong & Kannappan Palaniappan (2008) [3] proposed a Robust estimation Model for image Smoothing. This model uses anisotropic diffusion, bilateral filtering and robust function optimization. Here Edge preserving smoothing technique is incorporated with Graduated Non-convexity (GNC) to reduce local minima problems arise during edge preservation. This model reduces the effect of noise in an image by using non-linear filter for preserving edges.
Jacopo Grazzini & Pierre Soille (2009) [4] proposed twofold similarity measure from adaptive geodesic neighbourhoods for edge preservation. This method is used for both spatial and tonal information. It automatically determines the weights from the input image. In this, geodesic time function is computed over geodesic mask for estimating adaptive neighbourhood and a local measure of the twofold spatial and tonal similarity around every pixel. In addition to this, two efficient image-dependent algorithms are derived for improving the visual information in discrete images and avoid creation of spurious artifacts. It can potentially pre- serve important structural elements, such as multichannel edges, and eliminate degradations.
D.J. Withey et al (2009) [5] proposed a dynamic edge tracing with recovery and classification (DTRAC) in medical images. In this method, Edge detection and edge feature extraction are performed on the input image and the obtained results are used in target tracking algorithm and also includes process like State estimation, Data association. Edges are detected by using local and global image Information. This method provides results based on the metrics such as Tanimoto similarity measure to evaluate segmented regions, Hausdorff distance to evaluate boundary shapes, Snake automated partitioning (SNAP) and FMRIB automated segmentation tool (FAST) for hard segmentation. It avoids misclassification.
Shin-Min Chao & Du-Ming Tsai (2010) [6] proposed an improved anisotropic diffusion model for preserving edges and fine details of an image. This model incorporates local gray-level variance and gradient for adaptive smoothing. This model depends on adaptive function value k. If the specific area in an image has small gray-level variance, then, k has large and vice versa and finally stops the diffusion process. From this, edges and fine details in the image are preserved. It improves the quality of a noisy image. However, this method is not applicable for high level noise image and image with sparking impulse noise.
Rodrigo Moreno et al (2011) [7] proposed a tensor voting process for preserving edge in color image denoising. This process provides framework to encode color information. This method preserves the edge based on color differences, region uniformity and edginess. peak signal to noise ratio (PSNR) shoes better results on removing noise in the image.
Nóirín Duggan et al (2014) [8] discussed a simple boundary reinforcement technique for segmentation. First, image is approximated by piecewise constant function from Continuous Maximum Flow (CMF) algorithm. Then geodesic active contour (GAC) method is applied to detect boundary of an image. This approach is robust and preserve topology between the initial and target shape.
Gang Jun Tu & Henrik Karstoft (2015) [9] proposed a Logarithmic dyadic wavelet transform (LDWT) in edge detection and reconstruction. Logarithmic image processing (LIP) is used to separate gray tone and the gray level. By dyadic wavelet transform (DWT), edges can be easily detected because of its features like good locality and multi-scale identity. So, this model incorporates both LIP and DWT. LDWT is robust to low contrast edge detection.
A.K. Bhandari et al (2016) [10] developed about the optimal sub-band adaptive thresholding using adaptive differential evolution algorithm in edge preserved satellite image denoising. The author presented different optimization techniques and optimized an optimized adaptive thresholding function based framework for satellite image denoising using JADE for proper initialization of threshold and thresholding parameters. JADE is the new differential evolution algorithm which is varied from differential evolution (DE) in 3 ways. First uses the recent parent solution, then uses current-to-pbest mutation operator and finally uses dynamic values of mutation coefficient and crossover coefficient for preserving feature denoised image. This will provide fast convergence and easy implementation.

Nezamoddin N. Kachouie et al (2004) [11] presented a texture segmentation algorithm based on a hybrid filter bank. This algorithm includes Gabor filter bank and Discrete Cosine Transform (GDCT) for feature extraction process. Feature vectors that are obtained from this algorithm, are composed of both Gabor and DCT features. Principal components of the extracted features are evaluated by using competitive network to minimize the feature vector dimension. And finally, it classifies the

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quantized vectors. This GDCT provides better classification performance and reduces the error rate.

Antonella Di Lillo et al (2007) [12] presented a feature extraction method for texture classification. Here, texture features are first extracted and classified by using Principal Component Analysis (PCA) and Fisher coefficients. In PCA, feature space is transformed and information is compacted into the smallest number of dimensions by discarding redundant features. Hence, it minimizes the number of dimensions. In Fisher coefficients, these coefficients estimates discriminative power of each feature and remove the dimensions that do not help with the classification. Then at the segmentation process, the classifier is first trained on texture samples, and then tested on images composed of texture compositions. This method improves the robustness to resolution changes. However, there was no improvement in performance by combining PCA and Fisher coefficients.

Erik Bresch & Shrikanth Narayanan (2009) [13] proposed a method for region segmentation using frequency domain based algorithm. This algorithm is applied on a single channel MR data in k –space and it can be estimated using MR phantom experiment. In order to process multichannel MR data, this algorithm should be modified by including some data preprocessing steps, anatomically informed three-region geometrical model and anatomically informed gradient descent procedure. This algorithm is also used to detect contour of an image based on closed-form solutions using contour descriptors. However, it does not consider about optimization problem.

Jianjun Song et al (2011) [14] proposed an idea for binary image segmentation in frequency domain. The author considered the spectrum of original image and modifies the spectrum with Gaussian kernel function by using gaussian filter which smoothes the images. At last, segment theory was explained by using inverse discrete Frontier transformation. For binary image segmentation, only two gray scales are considered for reconstruction of original image. The algorithm used here is Gaussian frequency segmentation has good filtering and smoothing character of Gaussian filter. The segmentation result is based on internal uniformity degree. This method improved smooth and accuracy with minimum complexity.

K.Somasundaram & S.P.Gayathri (2012) [15] proposed a method based on Fast Fourier Transform (FFT) in brain image segmentation. Here, T2-weighted MRI image is used for segmentation. The image is first converted to the frequency domain. Then the filtered image is obtained from original image by applying FFT with high pass filter. Inverse transform function and thresholding technique are used to obtain the real part of filtered image and to remove the low intensity from it. At last, to segment the brain image, largest connected component (LCC) techniques are used. By using this technique, total misclassification rate and error rate get reduced.

Xiaoshan Yang et al (2012) [16] proposed a fast approach for image saliency detection using selected DCT coefficients. Here, both the spatial and feature dissimilarity measurements are used for computing saliency map of an image. By this computational result, author enhances the speed of context aware saliency detection approach by using selected DCT frequency coefficients. This approach reduces the runtime and improves the visual quality and computational efficiency.

Ashraf K. Helmy & Gh. S. El-Taweel (2015) [17] proposed a hybrid scheme for image segmentation in frequency domain. This scheme combines Self-Organizing Map (SOM) network and Modified Pulse-Coupled Neural Network (Modified-PCNN). Here, image segmentation is done in frequency domain using Shift Invariant Shearlet Transform (SIST). First, an input image is filtered and SIST is applied on filtered image to obtain low and high sub-band frequencies. Then feature vector is built using coarser coefficients and extracted the texture information. For classification of the input image coefficients, SOM is used. And then, PCNN is extended with SOM results to minimize the segmentation artefacts. This improves accuracy and reduces the classification error.

D. Ravi et al (2016) [18] introduced class-specific image segmentation. Here, quantized data of the Discrete Cosine Transform (DCT) in a Semantic Texton Forest based framework (STF) are combined together to provide information about colour and texture for by combining together colour and texture information for semantic segmentation. The main purpose of DCT is to provide complex textures including object and region represented in the frequency domain. It provides good accuracy for real time applications. It has high computational cost.

Katsuhiko SAKAUE et al [19] proposed Optimization approaches in computer vision and image processing. In this paper, they proposed a relaxation and regularization optimization method in both broad and narrow senses which are used in various fields and problems of computer and image processing. Also they proposed Genetic Algorithm as an optimization technique. These methods are used to minimize the errors due to segmentation and detection. This method is very complex and takes more time complexity.

Heinz Muhlenbein et al [20] proposed Predictive models for the Breeder Genetic Algorithm Continuous Parameter Optimization. In this paper, Breeder Genetic Algorithm (BGA) is introduced based on artificial selection which is more efficient for optimization than natural selection. This BGA controls the process of mutation and recombination in virtual breeders who have knowledge about all genes of his population. In this, Selection, Recombination and Mutation processes are discussed. For more population BGA is not more effective.

Ms. Sweta V. Jain et al [21] proposed Image optimization and prediction technique. This paper is focused on identifying global technique for image analysis and prediction. Here K-Means Clustering Algorithm is used to image segmentation and Query Optimization is used to

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find better information prediction. Initially the input data is divided into clusters and find the center of cluster and based on this segmentation obtained. Some valued functions are needed to be defined.

Ge Li et al [22] proposed a self-predictive parameter optimization algorithm in a real-time parallel image processing system. This paper proposed an adaptive load capacity balance strategy on the servo parameters optimization algorithm (ALBPO) to improve the computing precision and to achieve high detection ratio. They use load capacity functions (LC) to estimate the load for each processor and then make continuous self-adaptation towards a balanced status based on the fluctuated LC and compared with current load balance. This technique is very useful for parallel processed vision servo system for optimization of QoS for each processor, robustness and etc.

A.J. Pretorius et al [23] proposed visual parameter optimization for biomedical image analysis. They use default parameter optimization and optimal parameter optimization methods for visualization system to make poor quality segmentation and high quality segmentation. This is mostly used in bio-medical applications where users want accurate cell structure and regions of tissues.

Shan Shen et al [24] proposed MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural network optimization. In this paper, Fuzzy C-Means (FCM) clustering algorithm is proposed. A neighborhood attraction which is dependent on the relative location and features of neighbouring pixels is used to improve the segmentation. This technique is used only for MR image-based brain tumor analysis.

Maneesha Singh et al [25] proposed parameter optimization for image segmentation algorithms. In this paper, a novel solution based on classification complexity and image edge analysis for automatic selection of image segmentation algorithm parameter setting is proposed. This is based on classification complexity and image edge analysis.

This technique uses FCM, SOM and Gaussian Mixture Model (GMM) for image segmentation and parameter optimization.

A.Smith et al [26] proposed image segmentation scale parameter optimization and land cover classification using the Random Forest algorithm. This paper describes the use of Random Forest algorithm to evaluate a set of alternative segmentation scales during image segmentation. This algorithm is used for extraction of land use information from satellite images. But this algorithm does not detect any landscape changes and location of rare features.

Yu Liu et al [27] proposed Study on automatic threshold selection algorithm of sensor images. Initially the image is dividing into non-overlapping and connected set of pixels. Then for threshold selection bimodal algorithm, Iterative algorithm, OTSU algorithm and OTSU algorithm based on grey extension are used. This paper discussed about single threshold segmentation. For lattice images with small contrast, using OTSU method of grey extension to solve thresholds, conducting Binarization and solving standard deviation which is smaller.

Norazlina Ahmada et al [28] proposed threshold value in automatic learning style detection. This paper determines the threshold value based on patterns of behaviour for students. Patterns of behaviour are analyzed based on student's online learning activities. The threshold value depends on course structure, subject and experience of various students. The threshold value is mostly based on content visit and exercise visit and forum. This method is more useful for Learning Management System (LMS).

J. N. Kapur et al [29] proposed a new method for grey-level picture thresholding using the entropy of the histogram. In this paper, a threshold from the grey-level histogram of a picture has been derived by an algorithm that uses entropy method from information theory. It can be used for image segmentation. But if two different pictures have same grey-level histogram then the value of threshold is not discussed.

Yuan Been Chen et al [30] proposed image segmentation method using thresholds automatically determined from picture contents. This work develops an image segmentation method based on the modified edge-following scheme where different thresholds are automatically determined according to areas with varied contents in a picture. First, the iterative threshold selection technique is modified to calculate the initial-point threshold of the whole image or a particular block. Second, the quad-tree decomposition that starts from the whole image employs grey-level gradient characteristics of the currently-processed block to decide further decomposition or not. The contour thresholds are generated by analyzing the decomposed blocks, thus preventing the search from falling into the wrong path, and saving computational time.

Mithun Kumar PK et al [31] proposed automatically gradient threshold estimation of anisotropic diffusion for Meyer's watershed algorithm based optimal segmentation. The Meyer's Watershed algorithm is the most significant for a large number of regions separations but the over segmentation is the major drawback of the Meyer's Watershed algorithm. Over segmentation is removed by using anisotropic diffusion as a processing step which produces gradient threshold dynamically. This is very efficient and provides smooth image.

T. W. RIDLER et al [32] proposed picture thresholding using an iterative selection method. An object may be extracted from its background in a picture by automatically threshold selection. In this paper, threshold value may be selected as a result of iterative process and successive iterations provide cleaner extractions of the object region. This provides a picture contains an object and background occupying different average grey levels.

Yong Wu et al [33] proposed optimal threshold selection algorithm in edge detection based on wavelet transform. This paper presents an optimal threshold selection algorithm, which selects the de-noising threshold according to the turbulent degree of detected edge points,

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in edge detection based on wavelet transform. Initially Adjacent Domain Division Algorithm (ADDA) and Parabola Fitting Algorithm (PFA) are used to separate edge curves from each other after wavelet transform. Then entropies are computed corresponding to different thresholds according to number and length of all detected edge curves. The threshold which gives minimum entropy is selected as optimal threshold to filter the noise.

Jui-Cheng Yen et al [34] proposed a new criterion for automatic multilevel thresholding. The new criterion is based on two factors. One is discrepancy between threshold and original images and another is the number of bits required to represent threshold image. The classification number that the grey-levels should be classified and the threshold values can be determined automatically. This approach reduces searching complexity and computational complexity.

III. ENHANCED IMAGE DENOISING WITH EDGE PRESERVING SEGMENTATION (EID-EPS)

Non-harmonic analysis (NHA) is most widely used for suppressing the side lobes obtained while analyzing the frequency and effectively separates the original components from the noisy image. The main objective of the proposed work is:

1. Proper optimization of parameters is done by Self-Adaptive Parameter Optimization Algorithm to improve the computing precision and to achieve high detection ratio.
2. Iterative selection method is used for automatic selection of threshold value which provides clear information about extracted image. Threshold value may be selected as a result of iterative process and successive iterations.
3. Optimal sub-band adaptive thresholding using adaptive differential evolution algorithm is used which improves the denoising performance without affecting the edge details.

Estimation of stationary signals using frequency domain parameters, such as DFT or DCT coefficients to search for similar frequency patches as arbitrary position patches. These coefficients are thus used to extract a suitable frequency feature for image segmentation process.

In EID-EPS, NHA mainly concentrates on stationary signals. Image I with pixel coordinates (x, y) in the spatial domain is initially transformed into frequency domain using DCT [9] for enhancing the result of image segmentation along with fast implementation. After applying DCT to I, coefficients of an output image O with pixel coordinates (u, v) are achieved by,

$$O_{vu} = \frac{1}{4} A_v A_u \sum_{y=0}^{n-1} \sum_{x=0}^{n-1} I_{yx} \cos\left(v\pi \frac{2y+1}{2n}\right) \cos\left(u\pi \frac{2x+1}{2n}\right) \quad (1)$$

Such that $A_v = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } v = 0 \\ 1 & \text{else} \end{cases}$

and $A_u = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } u = 0 \\ 1 & \text{else} \end{cases}$

Where n represents the total number of pixels in an input image

Main advantage of DCT over DFT is that, DCT minimizes the number of multiplications. NHA determines these frequency coefficients using sinusoidal wave fitting. NHA in 2D sinusoidal model is expressed as:

$$I_{yx} = \hat{a} \cos\left(2\pi \frac{\hat{f}_x}{f_{xs}} x_1 + \frac{\hat{f}_y}{f_{ys}} x_2 + \hat{\varphi}\right) \quad (2)$$

Where $\hat{a}$ represents the amplitude of sinusoidal model, $\hat{f}_x$ and $\hat{f}_y$ represents the frequencies, f_{xs} and f_{ys} represents the sampling frequencies, $\hat{\varphi}$ represents the phase parameter of the model. Sampling frequencies f_{xs} and f_{ys} are given by,

$f_{xs} = \frac{1}{\partial x}$ and $f_{ys} = \frac{1}{\partial y}$

Thus, 2D NHA removes the frequency by reducing the mean squared error (MSE) between the target image and the model image. The parameters of frequency are determined by using the following equation:

$$f(\hat{a}, \hat{f}_x, \hat{f}_y, \hat{\varphi}) = \frac{1}{XY} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} ([I_{xy} - \hat{I}_{xy}])^2 \quad (3)$$

In DCT, the resolution of frequency is based on the size of the window and successfully separates the original signal from the noise signal. Frequency domain transformation for image denoising is done with the help of Patch. In general, smoothing effects of image denoising depends on the patch size. Edges merged with patches are converted to the sinc function using DCT. Part of the sinc function should be eliminated for analyzing the edges. Thus, edges are analyzed using thresholding process. Instead of giving fixed value for thresholding, our proposed technique incorporates the iterative threshold optimization [10] algorithm for automatic selection of optimal threshold values. The purpose of optimizing threshold values is for providing effective denoising result by removing the noise from the stationary signals. Iterative selection method is used for automatic selection of threshold value which provides clear information about extracted image. Threshold value may be selected as a result of iterative process and successive iterations.

A. Threshold optimization has following steps

1. Consider four corners of the scene as the first approximation
2. Switching function f (s) is utilized to route a digitized image into one of two integrators
3. The signal controlling the switch is referred to as a switching function f(s) and is in fact a thresholded (i.e., black and white) array of image points
4. If switching function f (s) = 0, then the input image signal is given to the integrator 1 and considered as the background
5. If switching function f (s) = 1, then the input image signal is given to the integrator 2 and it represents the object

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6. Calculating threshold by averaging integrator outputs
7. The process is repeated on the input image until the switching function, remains constant for further iterations.

After the deletion of stationary signals using iterative threshold selection algorithm, patches with similar frequencies are then considered for image segmentation. In image segmentation, image with noise is categorized into edge and texture region. Then, textures that are similar to one another are grouped into the same cluster and considered approximately equals to the stationary signals. Similarly, patches with same frequency are grouped together and considered as the stationary signals. Patches that are present on the boundary of segment can consists of different regions. In order to improve the segmentation result, parameter values used in the segmentation process should be optimized using Servo Parameters Optimization Algorithm [11].

B. Servo Parameters Optimization Algorithm

The proposed method should determine the values of several parameters based on the target images. Performance of proposed method is dependent on the values of these parameters. The values of the parameters should be chosen from the input images because the values of optimal parameters vary according to the nature of the input signal. The parameters of target detection and location algorithm for the control should be adjusted.

1) Control parameters set up:

A number of parameters can be set for the control of the performance of image processing in target detection and location algorithm. To uniformly evaluate the adjustment parameters, the control parameters are normalized as follows:

$$\overline{\lambda_n} = \frac{(\lambda_n - \lambda_{min}^n)}{(\lambda_{max}^n - \lambda_{min}^n)} \qquad (4)$$

where λ_{max}^n is the highest value of λ_n, λ_{min}^n is the lowest value of λ_n

2) Parameter Adjustment

Based on the normalized parameter results, self-adaptive adjustment is continuously performed based on the adjustment parameters, and the status of image acquisition. In order to improve the performance of NHA in converting non uniform shape into flexible shape, target regions R_T and remaining regions other than target regions $\widehat{R_T}$ are considered. For separating these two regions, weighting factor is used w (x, y) using binary data. If w (x, y) is equal to 0, then it represents the outer region of an image I. if w (x, y) is equal to 1, then it represents the target region of an image I. then the modified cost function is given by,

$$f(\hat{a}, \hat{f_x}, \hat{f_y}, \hat{\varphi}) = \frac{1}{XY} \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} w(x, y) \left(\left[I_{xy} - \widehat{I_{xy}} \right] \right)^2 \quad (5)$$

The values of $\hat{f_x}, \hat{f_y}, \hat{\varphi}$ are estimated for every iteration using Servo Parameters Optimization Algorithm. In some cases, segmentation of noisy image consists of fuzziness in the boundary of the region and the boundary of these fuzziness regions represents the edge region. Position of edges in the edge region is identified using canny edge detection. Before detecting the edge position, edge preserving smoothing method is used in which bilateral filtering is adapted. In bilateral filtering, weights are defined based on the pixel luminance difference between the pixel of interest and its nearby pixels. Bilateral filter is computed as:

$$B_F(x) = \frac{\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} I(\xi)\, w(\xi, x)\, d\xi}{\int_{-\infty}^{\infty} w(\xi, x)\, d\xi} \qquad (6)$$

Where I represents the input image, B_F represents the filter output image, ξ and x represents the frequency domain variables, $w(\xi, x)$ is given by,

$$w(\xi, x) = \exp\left(\frac{-(\xi - x)^2}{2\sigma_f^2}\right) \exp\left(\frac{-(I(\xi) - I(x))^2}{2\sigma_e^2}\right) \qquad (7)$$

where σ_f represents the standard deviation of filter intensity, σ_e represents the standard deviation of edge sensibility

After detecting the edge position, segmentation process is utilized in which parameter values are varied for every iteration using servo parameter optimization algorithm. For image segmentation, mean shift algorithm is used, which finds the density points of local maximum in the feature space. This mean shift algorithm does not need any information about number of segments. In kernel density function, mean shift algorithm is expressed as follows:

$$\hat{f}_{h,k(x)} = \frac{c_{k,d}}{nh^d} \sum_{n=1}^{n} k\left(\left\| \frac{x - x_i}{h} \right\|^2 \right) \qquad (8)$$

Where x represents the variable vector, x_i represents the sample vectors, k represents the kernel density function and it is derived as

$$g(x) = -k'(x) \qquad (9)$$

h represents the band parameter, $c_{k,d}$ represents the normalization constant

Convergence are achieved recursively to the local maximum and it is obtained from,

$$y_{j+1} = \frac{\sum_{i=1}^{n} x_i g\left(\left\| \frac{y_j - x_i}{h} \right\|^2 \right)}{g\left(\left\| \frac{y_j - x_i}{h} \right\|^2 \right)}$$

Thus the final segmentation of image using mean shift algorithm is done according to the distance measured between convergence points and its nearby points. Steps of mean shift algorithm are given as follows:

1. Getting convergence points $\{c_i\}$ through mean shift where i=1, 2,..., n
2. Grouping each convergence point c_i with its nearby points based on convergence and band parameter

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3. Final groups $\{G_p\}$ are achieved using weighted averaging.
4. Weights of each group are obtained using edge intensity
5. Give label $l_i = \{p|c_i \in c_p\}$ for each input vector c_i to utilize the indices of groups p.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, Experiments are conducted using LENA image and simulated in MATLAB. Comparison results are made between existing ID-EPS denoising and proposed EID-EPS denoising methods.

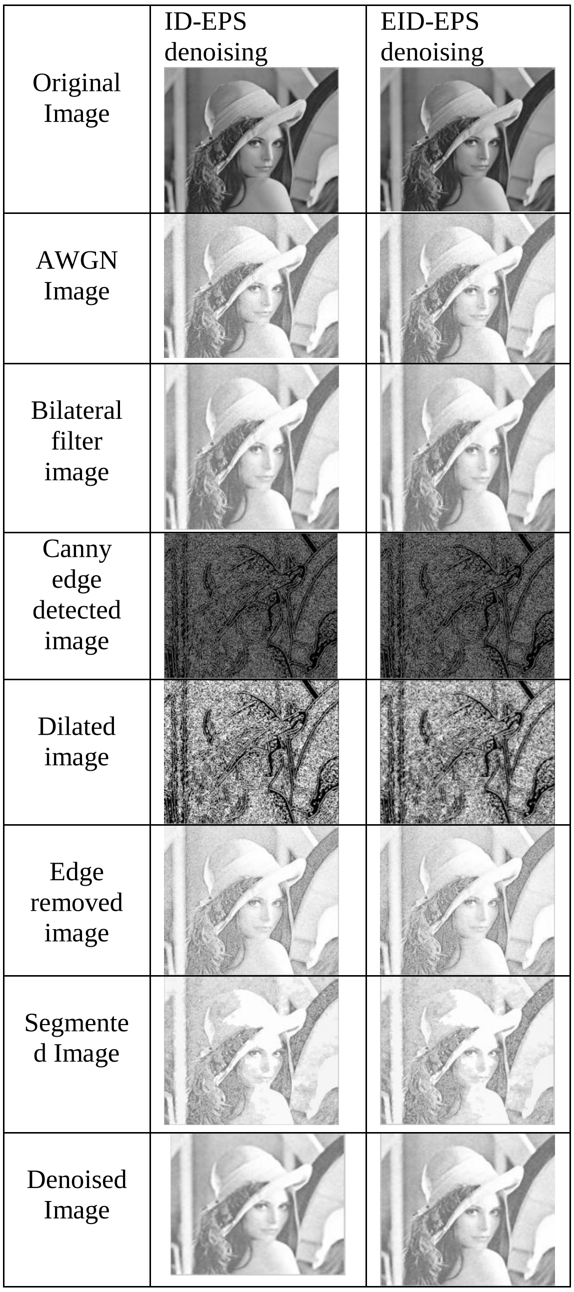

Figure1.Denoising Result

Parameters used for evaluating the performance of denoising methods are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

A. Mean Square Error (MSE)
MSE estimates the gray level difference between the pixels of original image I and denoised image $\hat{I}$ without taking the correlation between neighboring pixels. It is expressed as,

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}|I(i,j) - \hat{I}(i,j)|^2$$

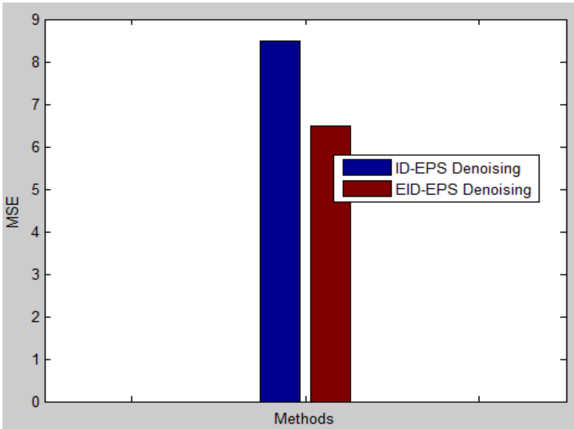

Figure2. Comparison result of MSE

Figure2 shows the comparison result of denoising techniques in terms of MSE on Lena image. Effective image denoising result is obtained in the frequency domain than in spatial domain. Noise is further reduced in developed denoising technique than in existing ID-EPS.

B. Peak Signal-to-Noise Ratio (PSNR)
PSNR is the ratio between index of each block and BER of secret bits. It is denoted by,

$$\text{PSNR (dB)} = 10\log_{10}\left(\frac{\text{Maximum possible pixel values in an image}}{\text{MSE}}\right)$$

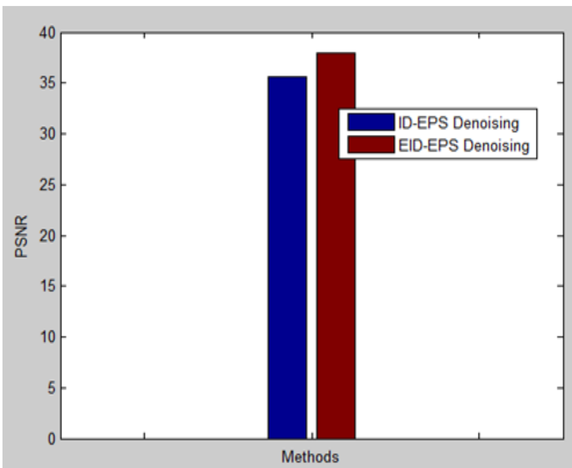

Figure3. Comparison result of PSNR

Figure3 shows the comparison result of denoising techniques in terms of PSNR on Lena image. The noise in the image can be minimized during edge preserving process. Hence with effective optimization algorithms, EID-EPS provides better result than the existing method.

C. Computational Time

The comparison of computational time between existing and proposed method is shown below.

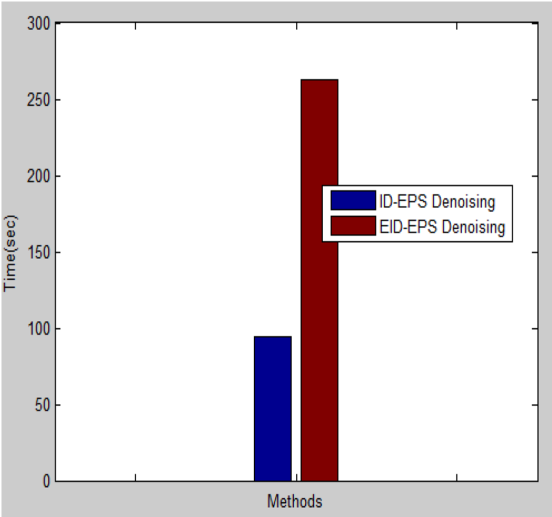

Figure4. Comparison result of Time

Figure4 shows the comparison result of denoising techniques in terms of time on Lena image. The figure shows that the computational time is high for EID-EPS denoising method. However, with effective optimization algorithms, EID-EPS provides better result than the existing method.

V. CONCLUSION

This paper presented an enhanced image denoising with edge preserving segmentation (EID-EPS) method in which segmentation is performed using frequency domain coefficient such as DCT to improve the segmentation result. Moreover, values of threshold and parameters are optimized for every iteration using iterative threshold selection and servo parameter optimization algorithm. Experiments are conducted and the performance of EID-EPS is evaluated using PSNR and MSE. The comparison result proved that, EID-EPS outperforms than the existing ID-EPD method.

VI. FUTURE ENHANCEMENT

The future extension of this research is to extend this work on video denoising and other restoration tasks such as deblurring and inpainting. This method can be extended for shape-adaptive color image and video denoising by taking into account the shape-adaptive patches and temporal redundancy across color components and frames. Moreover this model will be applying for unknown noise models for improvement than additive Gaussian noise.

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