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Enhancement of Gabor Directional Wavelet Edge Detection Method

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***Abstract* – This paper presents an approach for the enhancement of the performance of conventional Gabor directional wavelet edge detection method. The approach involves pre- and post-processing techniques. In the pre-processing technique, the input image is segmented by an optimal threshold method based on Shannon and Tsallis entropy. The segmented image is then applied to the Gabor directional wavelet edge detection method. In the post-processing, the output of the Gabor directional wavelet edge detection method is hysteresis thresholded. The lower and higher threshold values are computed using Otsu's method. The output greater than the higher threshold is taken as edge and, the lower than low threshold level is rejected. The output between the lower and higher is threshold using a single threshold value also computed by Otsu's method. Simulations results have been presented to show the impact of the proposed pre- and post-processing techniques in enhancing the performance of the Gabor directional wavelet edge detection method. The performance of the presented pre-, post-processed and simultaneous pre- and post-processed Gabor directional wavelet edge detection method are compared with the conventional Gabor and the commonly used Sobel and Canny methods. The results have shown that images with different edges can be best handled by the presented simultaneous pre- and post-processed Gabor directional wavelet edge detection method.**

***Keywords* – Canny, The Dyadic Wavelet Transform, Directional Wavelet, Gabor Wavelet.**

I. INTRODUCTION

Edges are the most principle features of images and edge detection is the main preprocessing tool in pattern recognition, image segmentation, and scene analysis. Edges are boundaries between different objects that are characterized by rapid change in intensity. Edge detection approach usually looks for singularities in images that can be characterized as discontinuities where the gradient approaches infinity [1]. However, nowadays, images are digital, so, edges in digital image have been defined as the local maxima of the gradient. Since rapid changes in images represent high frequency in the frequency domain, so, an edge detector can be basically a high pass filter that can be applied to extract or pass the edge pixels in an image. Edge detection therefore reduces the amount of image data by preserving only the pixels belonging to boundaries of objects. Gradient based edge detection methods simply compute the first and second derivatives and mark the pixels as an edge if the first derivative of the intensity is larger in magnitude than some threshold value, or the second derivative of the intensity has a zero crossing. These methods include Robert, Perwitt, Sobel, Laplacian of Gaussian (LOG), and Canny edge detectors [2]. They use some specifically designed operators to transform an image in spatial domain so that edges manifests themselves as maxima or zero-crossing points [2]. The image transform can be realized by discrete convolving the image with a set of directional derivative masks or operators. Most methods use 3x3 graident- or transform-operators which is computationally efficient. However, there are noises corrupting images, so, the 3x3 gradient-operator based method is very sensitive to noise and may detect points corresponding to noise as a part of edges, besides, some real edges may be missed [2].

Canny, to handle noise, he has used a Gaussian smoothing function prior to the graident-operator based transform. Therefore, this method is optimal for some edges such as step ones corrupted by white noise [3]. Moreover, Canny method follows several criteria in order to improve the gradient-operator based edge detection [3]. Despite the fact that Canny's method is known to many researchers as the better edge detection method, it still suffers from some practical limitations. Close edges may affect each other in the process especially when the smoothing Gaussian function is too wide which results in inaccurate edge locations and some edge losses. Besides, the hysteresis thresholding requires not only the trial and error adjustment of two thresholds to produce a satisfactory results for each different image but also requires the control of the imaging environment to assure the validity of the pre-adjusted thresholds [4].

Wavelet analysis is an efficient tool in signal and image processing. Wavelet analysis is implemented by filter banks which provide a multi-scales or multi-resolution analysis and singularities detection. So, it is an efficient tool for edge detection. However, Small-scaled filters are sensitive to edge signals but as well as to noise and large-scaled filters are robust to noise but could filter out fine details such as edges. Mathematically, it has been illustrated that signals and noise have different singularities and edge structures [8]. Therefore, multiple scales could be employed to detect varieties of edge structures [6]. Several wavelets such as Gabor and directional Gabor and wavelet-based techniques have been proposed for edge detection and denoising [9], [10], [11].

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This paper presents an approach to enhance the performance of an attractive Gabor directional wavelet edge detection method. This approach consists of pre- and post-processing techniques. The rest of the paper is organized as follows. In Section 2, previous works involving entropy based image segmentation, Gabor and Gabor directional wavelet edge detection methods are introduced. In section 3, the proposed pre-processed, post-processed, and simultaneous pre- and post-preprocessed Gabor directional wavelet edge detection methods are presented. Section 4 shows simulation results, which presents quantitative comparisons of the presented methods in comparison with widely used existing edge detection methods. In section 5, the conclusion is drawn.

II. Previous Works

A. Entropy Based Image Segmentation

The set of all source symbol probabilities is denoted by P, $P = \{p_1, p_2, p_3, \dots, p_k\}$. This set of probabilities must satisfy the condition $\sum_i^k p_i = 1, 0 \le p_i \le 1$. The average information per source output, denoted $S(z)$ [12],
Shannon entropy may be described as:

$$S(z) = -\sum_{i=1}^{k} p_i \ln(p_i) \quad (1)$$

Where k the total number of states. If we consider that a system can be decomposed in two statistical independent subsystems A and B, the Shannon entropy has the extensive property (additivity) $S(A+B) = S(A) + S(B)$, this formalism has been shown to be restricted to the Boltzmann-Gibbs-Shannon (BGS) statistics. Tsallis [13] has proposed a generalization of the BGS statistics which is useful for describing the thermo statistical properties of non-extensive systems. It is based on a generalized entropic form,

$$S_q = \frac{1}{q-1}\left(1 - \sum_{1=1}^{k} p_i^q\right) \quad (2)$$

Where the real number q is an entropic index that characterizes the degree of non-extensivity. This expression recovers to BGS entropy in the limit $q \longrightarrow 1$. Tsallis entropy has a non-extensive property for statistical independent systems, defined by the following rule [14]:

$$S_q(A+B) = S_q(A) + S_q(B) + (1-q)\,.S_q(A)\,.S_q(B) \quad (3)$$

Similarities between Boltzmann-Gibbs and Shannon entropy forms give a basis for possibility of generalization of the Shannon's entropy to the Information Theory. This generalization can be extended to image processing areas, specifically for the images segmentation, applying Tsallis entropy to threshold images, which have non-additive information content.

Let $f(x,y)$ be the gray value of the pixel located at the point (x,y). In a digital image $\{f(x,y) | x \in \{1,2,\dots,M\}, y \in \{1,2,\dots,N\}\}$ of size $M \times N$, let the histogram be $h(a)$ for $a \in \{0,1,2,\dots,255\}$ as G. Global threshold selection methods usually use gray level histogram of the image. The optimal threshold t^* is determined by optimizing a suitable criterion function obtained from the gray level distribution of the image and some other features of the image. Let t be a threshold value and $B = \{b_0, b_1\}$ be a pair of binary gray levels with $\{b_0, b_1\} \in G$. Typically b_0 and b_1 are taken to be 0 and 1, respectively. The result of thresholding an image function $f(x,y)$ at gray level t is a binary function $f_t(x,y)$ such that

$$f_t(x,y) = \begin{cases} b_0, & f(x,y) \le t \\ b_1, & f(x,y) > t \end{cases} \quad (4)$$

In general, a thresholding method determines the value t^* of t based on a certain criterion function. If t^* is determined solely from the gray level of each pixel, the thresholding method is point dependent [12]. Let $p_i = p_1, p_2, \dots, p_k$ be the probability distribution for an image with k gray-levels. From this distribution, we derive two probability distributions, one for the object (class A) and the other for the background (class B), given by:

$$p_A : \frac{p_1}{p_A}, \frac{p_2}{p_A}, \dots, \frac{p_t}{p_A}, p_B : \frac{p_1}{p_B}, \frac{p_2}{p_B}, \dots, \frac{p_k}{p_B} \quad (5)$$

$$P_A = \sum_{i=1}^{t} p_i \quad , \quad P_B = \sum_{i=t+1}^{t} p_i \quad (6)$$

The Tsallis entropy of order q for each distribution is defined as:

$$S_q^A(t) = \frac{1}{q-1}\left(1 - \sum_{i=1}^{t} p_A^q\right) \quad (7)$$

$$S_q^B(t) = \frac{1}{q-1}\left(1 - \sum_{i=t+1}^{t} p_B^q\right) \quad (8)$$

The Tsallis entropy $S_q(t)$ is parametrically dependent upon the threshold value t for the foreground and background. It is formulated as the sum each entropy, allowing the pseudo-additive property. We try to maximize information measure between the two classes (object and background). When $S_q(t)$ is maximized, the luminance level t that maximizes the function is considered to be the optimum threshold value [3].

$$t^*(q) = Arg_{t \in G} \max\left[S_q^A(t) + S_q^B(t) + (1-q).S_q^A(t).S_q^B(t)\right] \quad (9)$$

The threshold scheme follows this steps, Create a binary image by choosing a suitable threshold value using Tsallis entropy. The technique consists of treating each pixel of the original image and creating a new image, such that

$$f_t(x,y) = \begin{cases} 0, & f(x,y) \le t \\ 1, & f(x,y) > t \end{cases} \quad (10)$$

The following expression can be used to find the optimal threshold at $q \to 1$

$$t^*(1) = Arg_{t \in G} \max[S_1^A(t) + S_1^B(t)] \quad (11)$$

B. Gabor Wavelet Edge Detection

Let the mother wavelet be to be any smoothing function whose double integral is nonzero.We choose the Gaussian function as the smoothing function for wavelet $\theta(x,y)$

$$\theta(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\frac{1}{2}\left(\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2\right)} \quad (12)$$

Where σ is the standard deviation of the signal, we assume that $\mu_x = \mu_y = 0$ and $\sigma_x = \sigma_y = \sigma$

$$\theta(x,y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)} \quad (13)$$

We define two wavelets that are, respectively, the partial derivatives along the x and y of the 2-D smoothing function $\theta(x,y)$:

$$\Psi^1(x,y) = \frac{\partial\theta(x,y)}{\partial x} \;\; and \;\; \Psi^2(x,y) = \frac{\partial\theta(x,y)}{\partial y} \quad (14)$$

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Where $\Psi_s^1(x,y)$ and $\Psi_s^2(x,y)$ are scaled versions of $\Psi^1(x,y)$ and $\Psi^2(x,y)$ by scale parameter s. In addition, $s = 2^j, j \in z, j \in (-\infty, \infty)$.

$$\Psi_s^1(x,y) = \frac{1}{s^2}\Psi_1\left(\frac{x}{s},\frac{y}{s}\right), \Psi_s^2(x,y) = \frac{1}{s^2}\Psi_2\left(\frac{x}{s},\frac{y}{s}\right) \quad (15)$$

Let the 2D signal $f(x,y) \in L^2(R^2). L^2(R^2)$ denotes the Hilbert space of 2D square-integrable functions, such that

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}|f(x,y)|dx\,dy < \infty \quad (16)$$

The separable and isotropic 2-D wavelet transform [17] of a finite energy image $f(x,y) \in L^2(R^2)$ is defined by

$$W_s^1 f(x,y) = (f * \Psi_s^1)(x,y), W_s^2 f(x,y) = (f * \Psi_s^2)(x,y) \quad (17)$$

We can easily prove that

$$\begin{pmatrix} W_s^1 f(x,y) \\ W_s^2 f(x,y) \end{pmatrix} = s\begin{pmatrix} \frac{\partial}{\partial x}(f * \theta_s)(x,y) \\ \frac{\partial}{\partial y}(f * \theta_s)(x,y) \end{pmatrix} = s\nabla(f * \theta_s)(x,y) \quad (18)$$

If we want to locate the positions of rapid variations (edges) of an image$f(x,y)$, we should consider the local maxima of the gradient magnitude at various scales which is given by

$$M_s f(x,y) = \left\|\begin{pmatrix} W_s^1 f(x,y) \\ W_s^2 f(x,y) \end{pmatrix}\right\| = |s\nabla(f * \theta_s)(x,y)| \quad (19)$$

$$M_s f(x,y) = \sqrt{|W_s^1 f(x,y)|^2 + |W_s^2 f(x,y)|^2} \quad (20)$$

$s = 2^j, j \in z, j \in (-\infty, \infty)$. The function $M_s f(x,y)$ is also called the modulus of the wavelet at scale s [16]. A point (x,y) is a multi-scale edge point at s if the magnitude of the gradient $M_s f(x,y)$ attains a local maximum there along the gradient direction $A_s f(x,y)$, defined by

$$A_s f(x,y) = \tan^{-1}\left(\frac{W_s^2 f(x,y)}{W_s^1 f(x,y)}\right) \quad (21)$$

The angle $A_s f(x,y)$ can be used to recover the two components $W_s^1 f(x,y)$ and $W_s^2 f(x,y)$ from the modulus $M_s f(x,y)$. Like the non-maximum suppression in Canny edge detection, we detect the points where the modulus of $\nabla(f * \theta_s)(x,y)$ is locally maximum. At each scale s, the modulus maximum of the wavelet transform are thus defined as points (x,y) where the modulus image $M_s f(x,y)$ is locally maximum, along the gradient direction given by $A_s f(x,y)$.these modulus maxima are inflection points of $(f * \theta_s)(x,y)$. We record the position of each modulus maximum and the values of $M_s f(x,y)$ and $A_s f(x,y)$ at the corresponding locatin [16]. After obtaining the local modulus maxima and the angle information, we now can compute the edge image at scale s by thresholding the magnitude function as:

$$E_s(x,y) = f(x) = \begin{cases} 0, & \|W_s f(x,y)\| < T \\ 1, & \|W_s f(x,y)\| \geq T \end{cases} \quad (22)$$

Where T is the threshold value that separates the image into the edges and the background, and can be determined using Otsu's method [17].

The most applications of the edge detection require the following criteria: [2] [15][16]

(1) Multi-resolution: The edge detection method should allow the resolution of edges to be variable. The classical edge detector cannot do it, but the wavelet transform can.

(2) Localization: The basis elements used in the edge detection should be well concentrated in both the spatial and frequency domains. The Fourier transform is lack of this property.

(3) Directionality: The edge detection technique should contain the basis functions oriented at the variety of directions, mot just horizontal and vertical directions.

(4) Anisotropy: To capture the smooth contours in the images, the edge detection technique should contain the basis functions with variety of shapes, in particular with different aspect ratios.

The first two criteria are successfully provided by the gabor wavelet transform which is separable and isotropic, but it is lack of the properties (3) and (4). So, if we encounter with and edge which is not in the horizontal or vertical direction and it is very smooth, then the traditional wavelet-based scheme will have poor performance. Therefore, non-separable directional wavelet transform such as the Gabor directional wavelet transform are needed to solve this problem. It is obvious that, Gabor directional wavelet require more computations than the gabor wavelet transform which explained in section 2.2 that requires only two wavelet transform computations at the *x* and *y* directions.

C. Gabor Directional Wavelet Edge Detection

A directional mother wavelet is a function $\psi(x,y) \in L^2(R^r)$ where its Fourier transform $\hat{\psi}(\omega_x, \omega_y)$ has support in a convex cone in the spatial frequency space, with apex at the origin. An example of this type is the Gabor directional or Morlet wavelet [16]. A Gabor directional mother wavelet is a Gaussian modulated by a sinusoid. It is a non-orthogonal wavelet with the modulated sinusoidal frequency of ω_0 and the standard deviations σ_x and σ_y which is expressed as:

$$\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right) + j\omega_0 x\right) \quad (23)$$

Through this representation, we can write the directional wavelet transform of 2D signal (image) $f(x,y)$ at scale s and orientation θ as:

$$W_{s,\theta} f(x,y) = (f * \psi_{s,\theta})(x,y) \quad (24)$$

Where the Gabor directional wavelet $\psi_{s,\theta}(x,y)$, obtained by dilation and rotation of the mother function $\psi(x,y)$. Thus

$$\psi_{s,\theta}(x,y) = \frac{1}{s}\psi\left(\frac{x'}{s},\frac{y'}{s}\right) \quad (25)$$

$$x' = x\cos\theta + y\sin\theta, y' = y\cos\theta - y\sin\theta \quad (26)$$

For the edge detection, we compute the wavelet transform of the image at scale $s = \alpha^m, for\ \alpha = 2, m = 0,1,\ldots,M-1$ and orientations $\theta_n = \frac{n\pi}{N}, for\ n = 0,1,\ldots,N-1$. M and N denote the total numbers of scales and the orientations. Therefore the Gabor directional wavelet functions $\psi_{m.n}(x,y)$ are designed so to ensure that the half-peak magnitude supports of the filter responses in the frequency spectrum touch one another [16]. By doing this, it can be ensured that the filters will capture the maximum information with minimum redundancy. After getting $W_{s,\theta} f(x,y)$, we choose the

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maximum value of the transform through non-maximum suppression:

$$W_m f(x,y) = Max_n \left(W_{m,n} f(x,y)\right) \quad (26)$$

If this maximum value us greater than the threshold then it is an edge point, else it is ignored. Fig. 1 shows a schematic block diagram for the Gabor directional wavelet edge detection.

III. Pre- and Post-processed Gabor Directional Wavelet Edge Detection

In the following subsections the proposed pre- and post-processing techniques for the enhancement of Gabor directional wavelet edge detection method are explained.

A. Pre-processed Gabor Directional Wavelet Edge Detection

In the preprocessing technique, the input original image is segmented by an optimal threshold method based on Shannon and Tesllisa Entropy as explained in section 2.1. The segmented image is then applied to the Gabor directional wavelet edge detection method. Fig. 2 show schematic block diagram of the Preprocessed Gabor directional wavelet edge detection method.

B. Post-processed Gabor Directional Wavelet Edge Detection

In the post-processing Gabor directional wavelet edge detection, the original image is applied to the Gabor directional wavelet edge detection method. Then the output image proposed to be hysteresis threshold. That is, the lower and high threshold values are computed using Otsu's method. The output greater than the higher threshold is taken as edge and, the lower than low threshold level is rejected. The output between the lower and higher is threshold using a single threshold value also computed by Otsu's method. Fig. 3 shows a schematic block diagram for the post-preprocessing Gabor directional wavelet edge detection technique.

C. Pre- and post-processed Gabor Directional Wavelet Edge Detection

In the simultaneous pre- and post-processed Gabor directional wavelet edge detection method, the original image is first pre-processed as described in 3.1, then the segmented image after the pre-processing is applied to the Gabor directional wavelet edge detection method, and finally the output of the Gabor directional wavelet method is post-processed as described in section 3.2. Fig. 4 shows a schematic block diagram for the pre- and post-processed Gabor directional wavelet edge detection method.

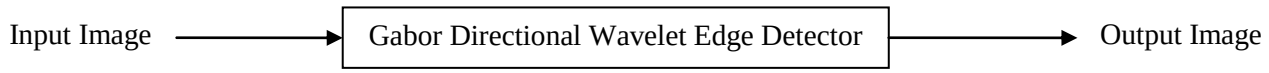

Fig.1. Gabor Directional Wavelet Edge Detection Method

Fig.2. Pre-processed Gabor directional wavelet edge detection Method

Fig.3. Post-processed Gabor Directional Edge Detection Method

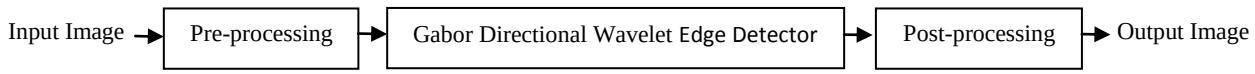

Fig.4. Pre- and Post-processed Gabor Directional WaveletEdge Detection Method

IV. Simulation Results

The objective of this simulation is to show the performance of the enhancement Gabor directional wavelet edge detection in comparison with widely used methods such as original Gabor wavelet, Sobel, and Canny edge detection methods. The Berkeley Segmentation Dataset (BSD) images [17] and respective ground truths are used in this simulation. In the pre-processing (image segmentation) technique the Tsallis entropy index q is experimentally determined to be 0.1. Fig. 5 shows pairs of the original and the segmented images after the pre-processing is carried out. In the post-processing, the total number of orientations N is selected to be 6; total number of scales M is selected to be 2; angular resolution is selected to be $\pi/6$, width and height of filter is assigned to be 45, frequency is selected to be $\sqrt{2}$. To measure quantitatively the performance of each method, the Performance Ratio (PR), Peak Signal to Noise Ratio (PSNR), False Alarm Count (FAC), Miss Count (MSC), and Figure of Merit (FoM) are used. The PR is defined as the ratio of true to false edges [18].

$$\mathrm{PR} = \frac{\text{True Edges (Edge pixels identified as Edges)}}{\text{False Edges + Edge pixels identified as non-edge pixels}} \times 100 \quad (27)$$

The FoM is defined by

$$FoM = \frac{1}{\max(I_A, I_I)} \sum_{i=1}^{I_A} \frac{1}{1+d_i \propto^2} \quad (28)$$

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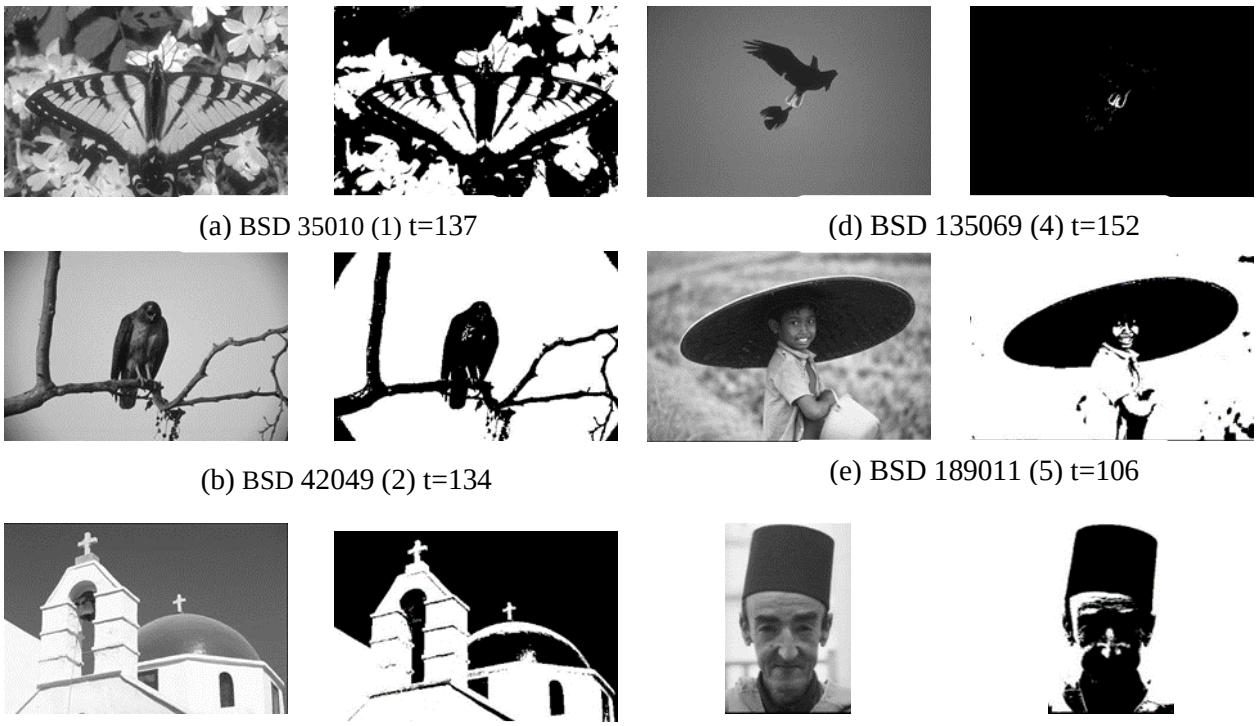
where, false edges are the non-edge pixels identified as edges, $I_A$is the detected edges, I_I $is\ the$ ideal edges, d is the distance between actual and ideal edges and $\propto$ is the penalty factor for displaced edges. (PR, PSNR, FoM), higher the value of these parameters better the result is. (MSC, FAC), lower the value of these parameters better the result is. Figs. 6-10 show BSD original image,its Ground Truth, output of Gabor directional wavelet edge detection method, output post-processed Gabor directional wavelet edge detection method, pre-processed Gabor directional wavelet edge detection method, simultaneous pre- and post-processed Gabor directional wavelet edge detection method, Canny, and Sobel methods. It is apparent that the pre- and post-processing enhances the performance of the original Gabor directional wavelet edge detection method. Figs 11-16 show charts of the performance quantitative values of different methods. It is clear that the pre- and post-processed Gabor directional wavelet edge detection method provides superior performance values than the original Gabor directional wavelet, Sobel, and Canny edge detection methods.

V. CONCLUSION

In this paper a pre- and-post processing techniques have been presented to enhance the performance of Gabor directional wavelet edge detection method. In the pre-processing technique we have used an entropy based segmentation technique prior to the original Gabor directional wavelet edge detection method. In the post-processing techniques the output of Gabor edge detection method is hysteresis threshold using Otsu's method. Simulation results have shown that pre- and-post processing could enhance the performance of the Gabor directional wavelet edge detection methods, and provide better performance than the Sobel and Canny edge detection methods.



(a) BSD 35010 (1) t=137

(d) BSD 135069 (4) t=152

(b) BSD 42049 (2) t=134

(e) BSD 189011 (5) t=106

(c) BSD 118035 (3) t=142

(f) BSD 189080 (6) t=137

Fig.1. Pairs of Original (right) and Segmented (left) (Pre-pocssed) Images (a) BSD 35010 (1) t=137 (b) BSD 42049 (2) t=134 (c) BSD 118035 (3) t=142 (d) BSD 135069 (4) t=152 (e) BSD 189011 (5) t=106 (f) BSD 189080 (6) t=137

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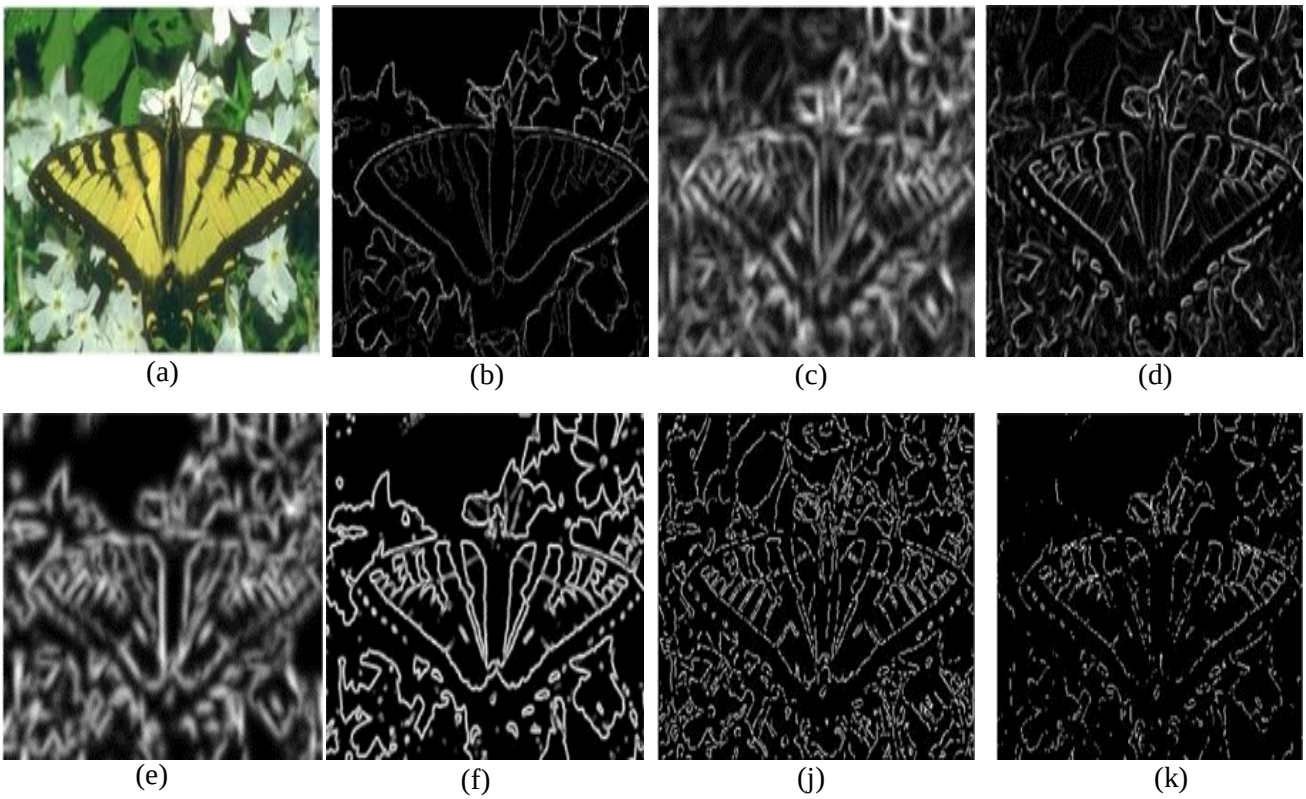

Fig.2. (a) BSD image 35010 (1), (b) Ground Truth, (c) Gabor Edge Detection Method, (d) Post Processed Gabor Edge Detection Method, (e) Pre-Processed Gabor Edge Detection Method, (f) Pre- and Post-Processed Gabor , (j) Canny, and (k) Sobel.

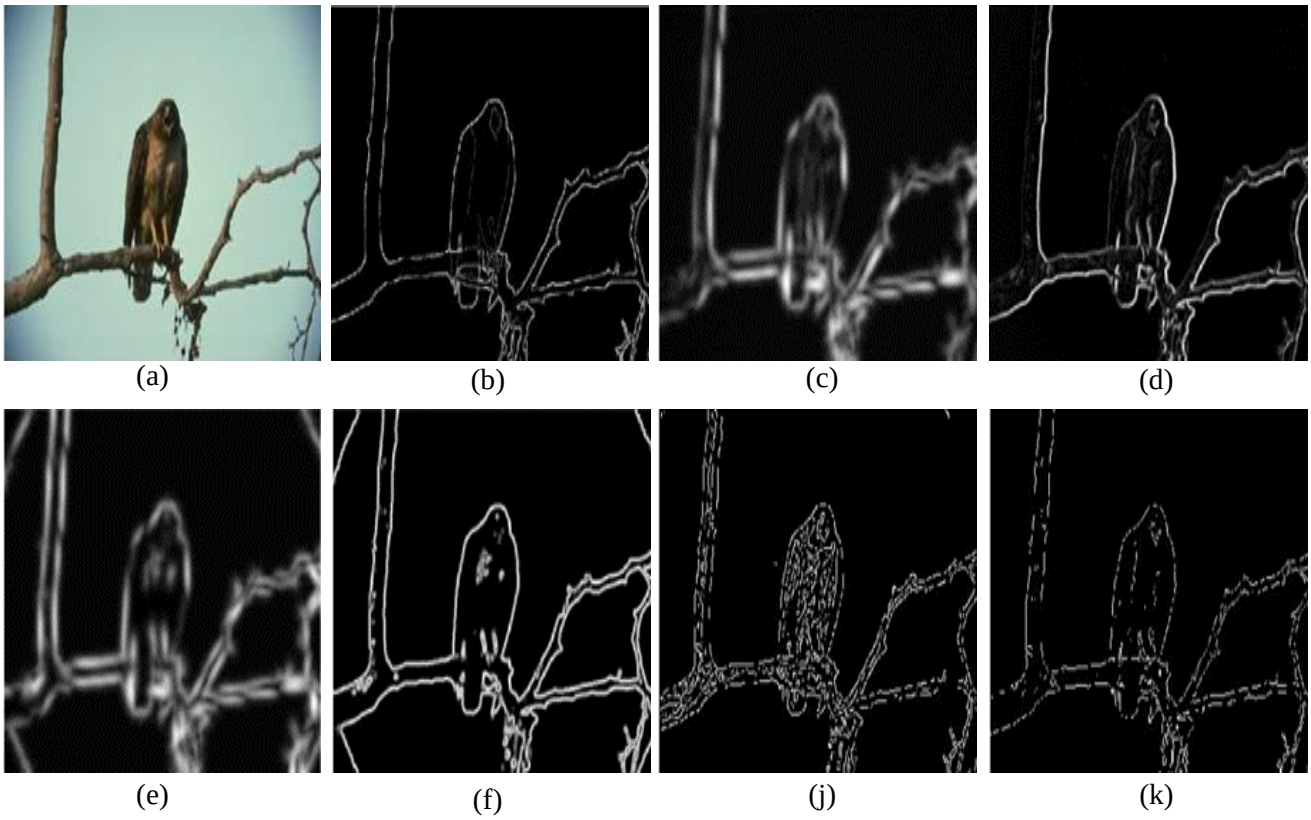

Fig.3. (a) BSD image 42049 (2), (b) Ground Truth, (c) Gabor Directional Wavelet, (d) Post Processed Gabor Directional Wavelet, (e) Pre-Processed Gabor Directional Wavelet, (f) Pre- and Post-Processed Gabor Directional Wavelet, (j) Canny, and (k) Sobel.

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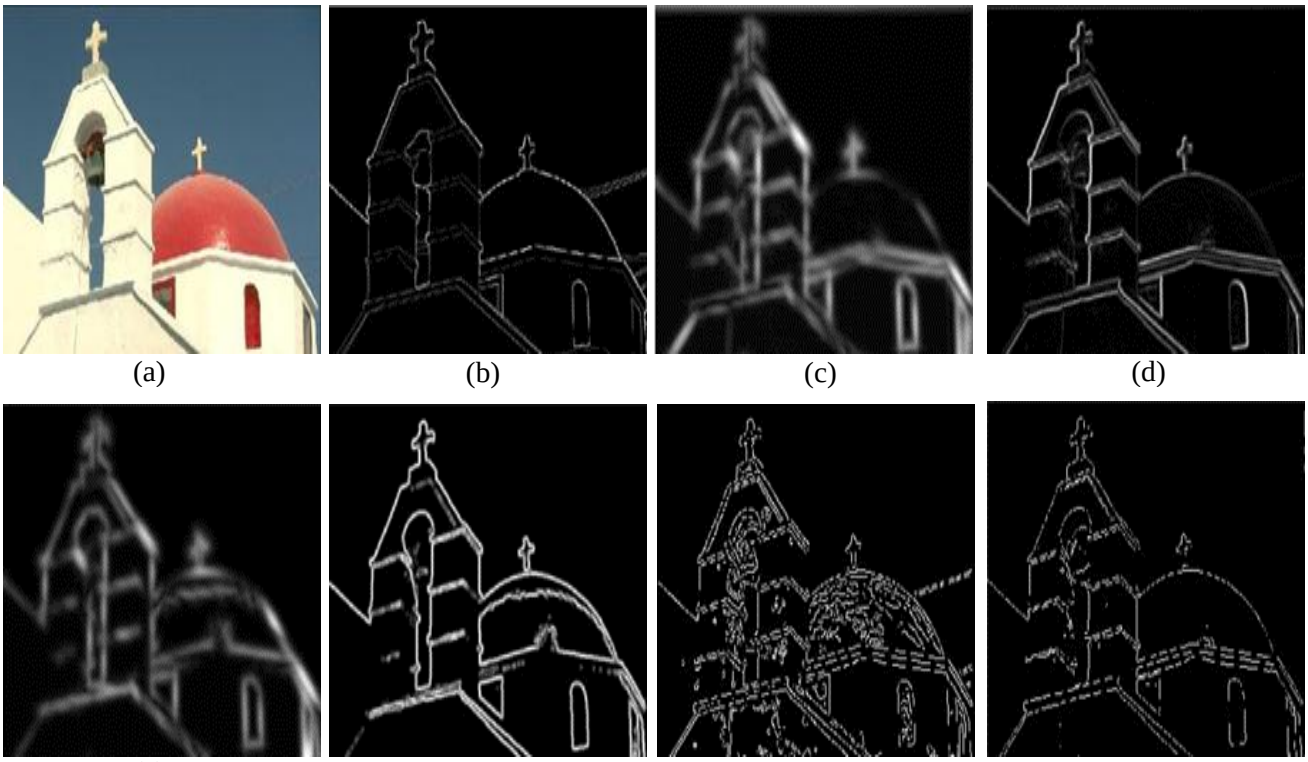
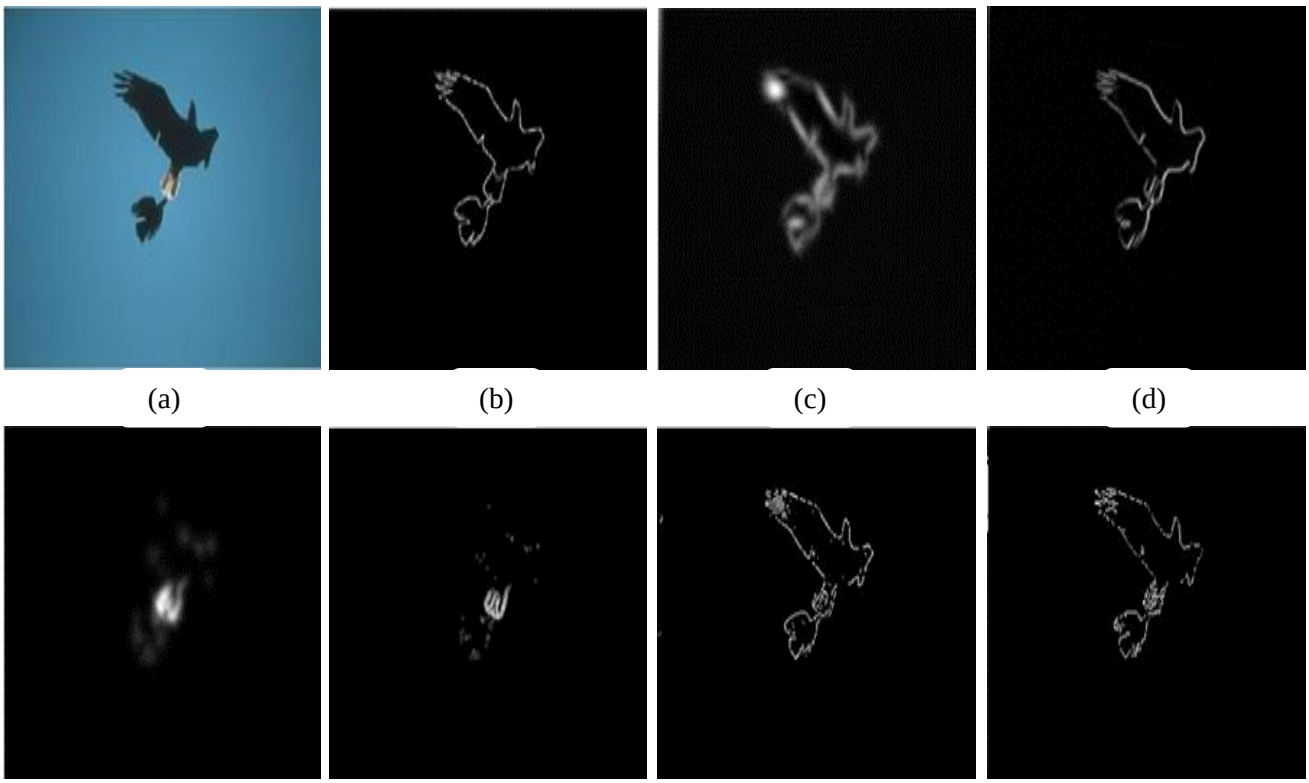


(a) (b) (c) (d)

(e) (f) (j) (k)

Fig.4. (a) BSD image 118035 (3), (b) Ground Truth, (c) Gabor Directional Wavelet, (d) Post Processed Gabor Directional Wavelet, (e) Pre-Processed Gabor Directional Wavelet, (f) Pre- and Post-Processed Gabor Directional Wavelet Wavelet, (j) Canny, and (k) Sobel.



(a) (b) (c) (d)

(e) (f) (j) (k)

Fig.5. (a) BSD image 135069 (4), (b) Ground Truth, (c) Gabor Directional Wavelet, (d) Post Processed Gabor Directional Wavelet, (e) Pre-Processed Gabor Directional Wavelet, (f) Pre- and Post-Processed Gabor Directional Wavelet, (j) Canny, and (k) Sobel.

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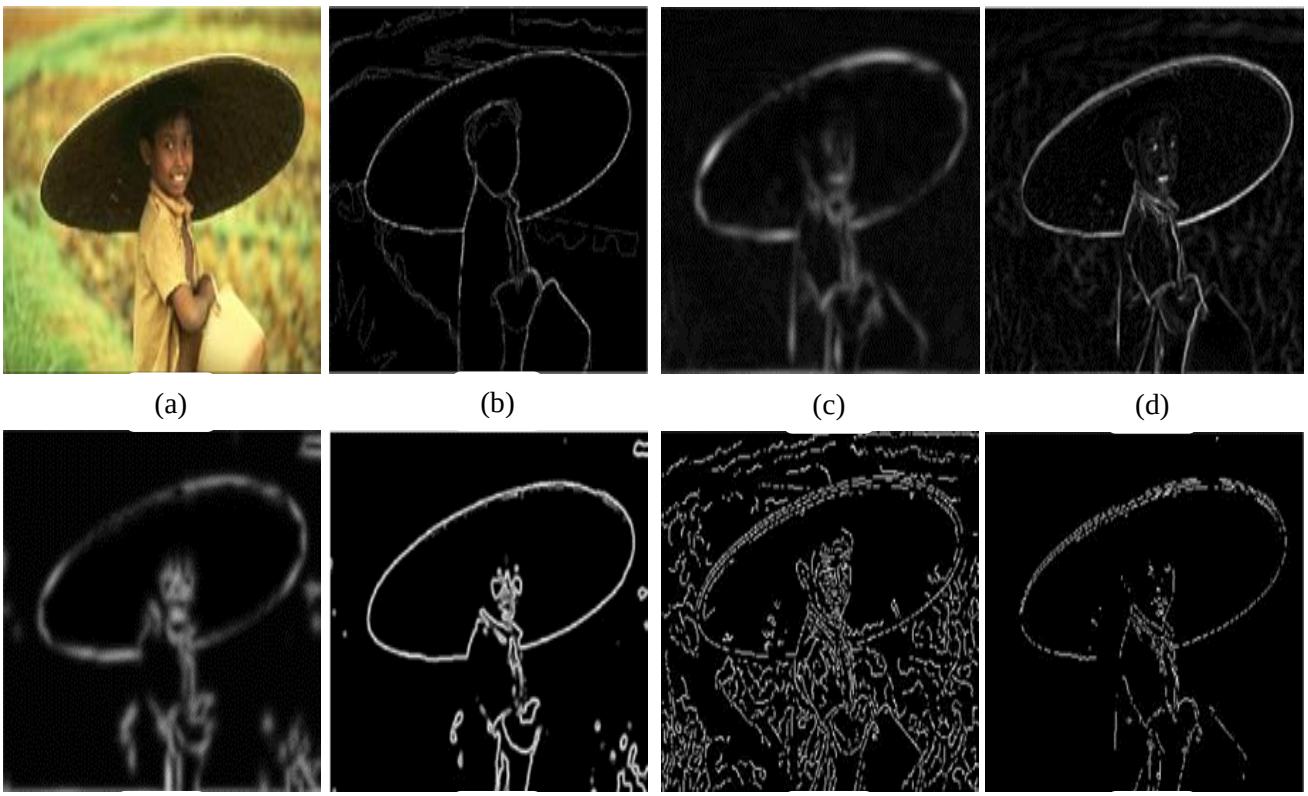
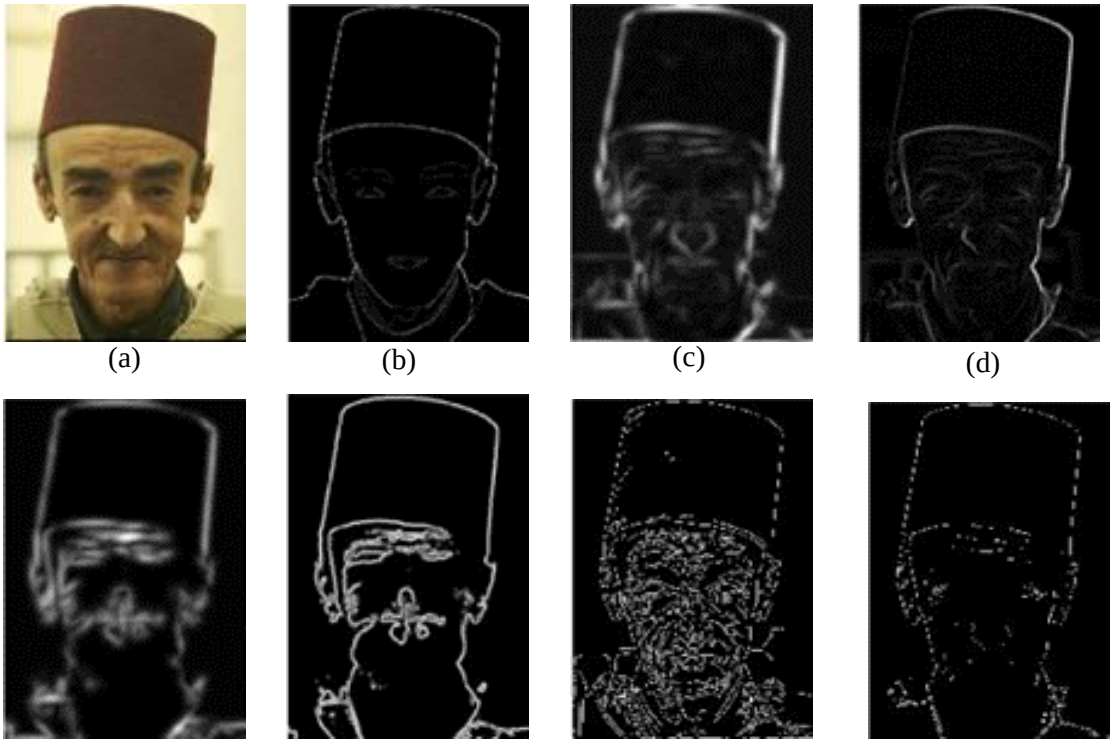


(a) (b) (c) (d)

(e) (f) (j) (k)

Fig.6. (a) BSD image 189011 (5), (b) Ground Truth, (c) Gabor Directional Wavelet, (d) Post Processed Gabor Directional Wavelet, (e) Pre-Processed Gabor Directional Wavelet, (f) Pre- and Post-Processed Gabor Directional Wavelet, (j) Canny, and (k) Sobel.



(a) (b) (c) (d)

(e) (f) (j) (k)

Fig.7. (a) BSD image 189080 (6), (b) Ground Truth, (c) Gabor Directional Wavelet, (d) Post Processed Gabor Directional Wavelet, (e) Pre-Processed Gabor Directional Wavelet, (f) Pre- and Post-Processed Gabor Directional Wavelet, (j) Canny, and (k) Sobel.

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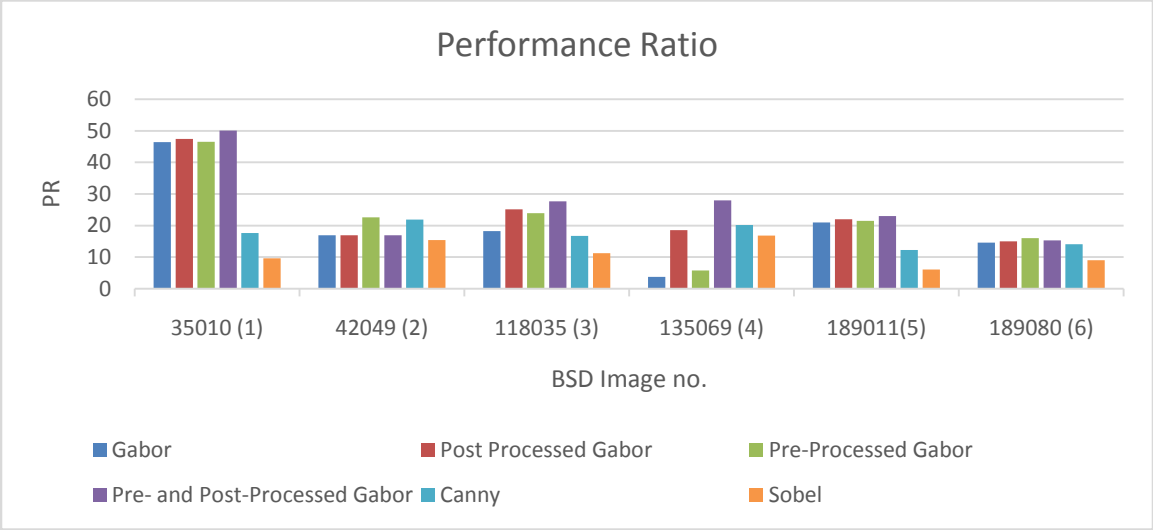

Fig.8. Performance Ratio

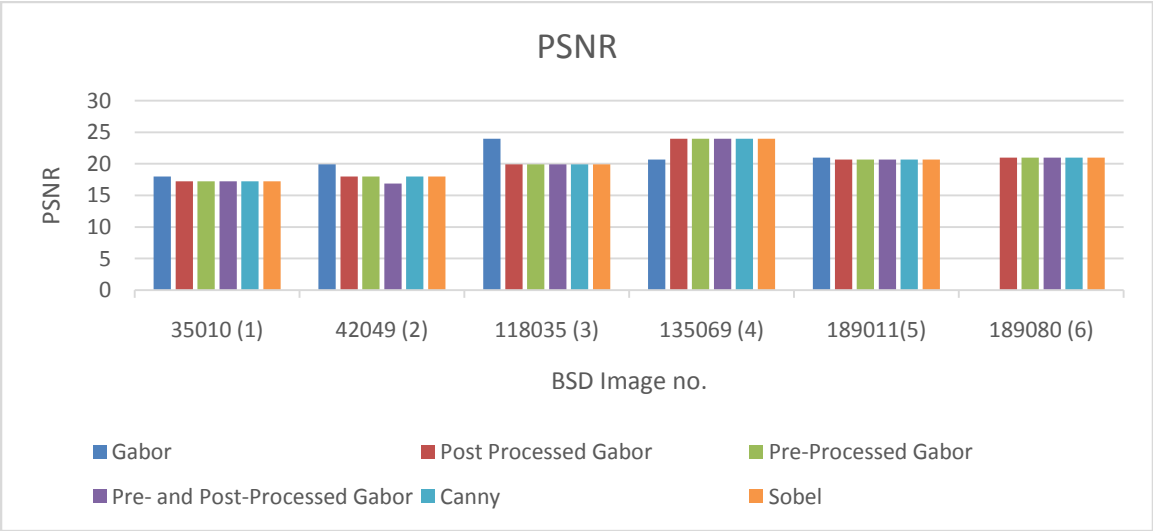

Fig.9. Performance Signal to Noise Ratio

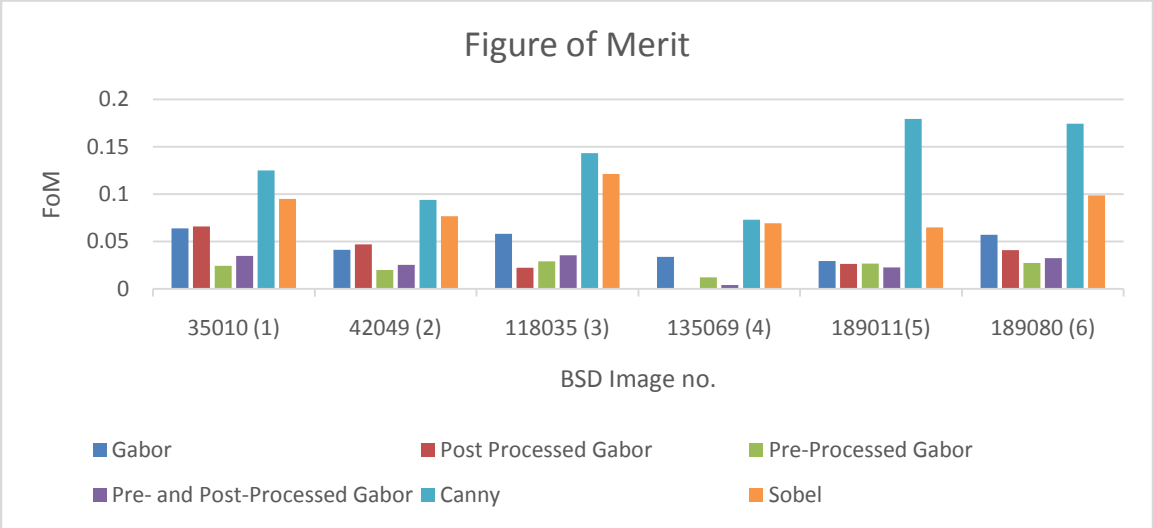

Fig.10. Figure of Merit

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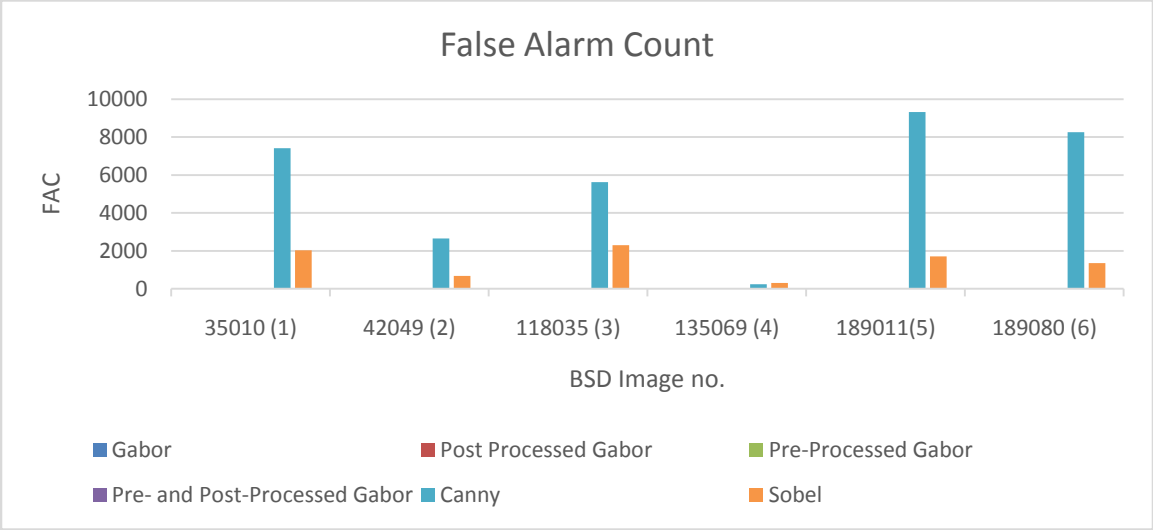

Fig.11. False Alarm Count

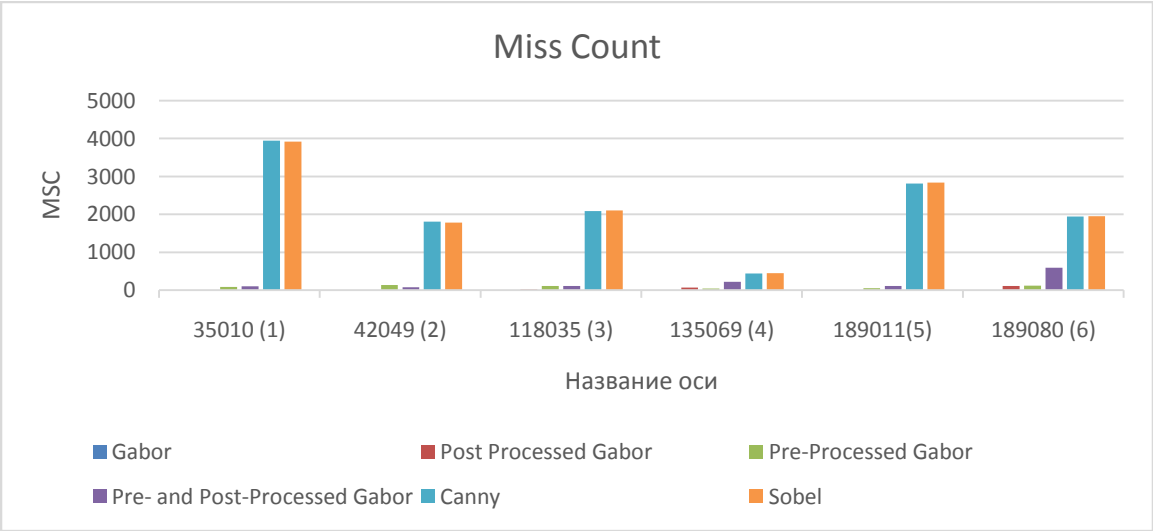

Fig.12. Miss Count

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