# A COMPREHENSIVE STUDY OF EDGE DETECTION TECHNIQUES IN IMAGE PROCESSING APPLICATIONS USING PARTICLE SWARM OPTIMIZATION ALGORITHM

**M. S. CHELVA[a1] AND A. K. SAMAL[b]**

[a]Computer Science, Swami Vivekananda Mahavidlya, Udgir, Maharastra, India
[b]Department of Computer Science & Engineering, Trident Academy of Technology, Bhubaneswar, Odisha, India

## ABSTRACT

**Edge detection is an important task in image processing. Edge is defined as the boundary between two regions separated by two relatively distinct gray level properties. Traditional edge detection methods give rise to the exponential increment of computational time. In this paper, edge detection in gray level images is done by using Renyi entropy and particle swarm optimization (PSO) algorithm. The Renyi entropy is a one-parameter generalization of the Shannon entropy. Here Renyi entropy was calculated for the one-dimensional histogram of the images. PSO is an efficient and powerful population-based stochastic search technique for solving optimization problems, and this has been widely applicable in many scientific and engineering fields. The selection of the initial population in a population-based heuristic optimization method is most important, as it affects the search for a number of iterations and has an influence on the final solution. If the prior information about the optima is not available, then the initial population is selected randomly using a pseudorandom numbers. The main advantage of PSO algorithm is its simple in structure, easy to use, speed and robustness.**

**KEYWORDS:** Particle Swarm Optimization (PSO), Renyi Entropy, Shannon Entropy, Edge Detection & Classification.

Edge detection is a method which identifies the points in a digital image at which the brightness of the image changes clearly [Pattanaik et. al., 2015]. Edge detection is the boundary between two regions separated by two relatively distinct grey level properties. The applications of edge detection such as image enhancement, water marking, compression, restoration, etc. has been presented in [Singh and Singh, 2008]. The traditional edge detection algorithms have been developed based on computation of the intensity gradient vector and it is very sensitive to noise in the image. For decreasing the noise some spatial averaging may be combined with differentiation that is known as LoG (Laplacian of Gaussian operators) function as a filter [Wang and Shuyuan, 2005 & Singh and Singh, 2008]. But this method used a 2-D linear filter which is similar to second order derivatives and that also sensitive to noise [Zhang et. al., 2005]. And the magnitude of the images produces double edges and gives the undesirable effect due to incomplete segmentation. For this reason laplacian combined with smoothing and find the edges via zero crossing and it also time taking. But the proposed a technique which is based on the information theory known as Renyi entropy [Pattanaik et. al., 2015].

Renyi entropy decreases the computation time. To compare the result of Renyi entropy we proposed a new method which is based on optimization algorithm i.e., PSO algorithm which is a optimization algorithm. PSO is an evolutionary algorithm and it is use to find out the near optimal solutions. For minimizing the total cost and maximize the possible reliability most of the optimization algorithm is used.

The rest of the paper is organized as follows: we present a survey of literature in Section 2 and discussion on various background concepts related to image information contents in Section 3. In Section 4, we discuss the PSO technique In Section 5, we discussed the proposed methodology and the analysis of results of the simulation based study of edge detection. Finally, in Section 6 we present concluding remarks on the outcome of this work.

## SURVEY OF LITERATURE

There have been many works done in the area of edge detection techniques in image processing applications using varieties of methods and techniques. In this section, with new and more efficient methods of edge detection approaches in image processing applications than the existing and currently practiced methods that shows better performance, we present an extensive survey of research literature and related publications reflecting status of existing and recent works going on in this field.

M. P. de Albuquerque et al. [2004] have introduced that, the maximum entropy principle has a relevant role in image processing, in a particular threshold and image segmentation. Different entropy formulations are available to this purpose; one of them is based on the Tsallis non extensive entropy. Here, we proposed a discussion of its use for bi- and multilevel-threshholding. Sahoo and Arora [2004] have presented

[1]Corresponding author

a new thresholding technique based on two-dimensional Renyi's entropy. The two-dimensional Renyi's entropy was obtained from the two-dimensional histogram which was determined by using the gray value of the pixels and the local average gray value of the pixels. This new method extends a method due to Sahoo et al. [1988] and includes a previously proposed global thresholding method due to Abutaleb. Further, our method extends a global thresholding method due to Chang et al. to the two-dimensional setting. The effectiveness of the proposed method is demonstrated by using examples from the real-world and synthetic images. Shrivakshan and Chandrasekar [2012] have proposed that, Edge detection refers to the process of identifying and locating sharp discontinuities in an image. Hence, edge detection is a vital step in image analysis and it is the key of solving many complex problems. Edge detection is a fundamental tool used in most image processing applications to obtain information from the frames as a precursor step to feature extraction and object segmentation. The edge detection has been used by object recognition, target tracking, segmentation, data compression, and also helpful for matching, such as image reconstruction and so on. Edge detection methods transform original images into edge images benefits from the changes of grey tones in the image. In this research paper, two edge detection algorithms namely Canny edge detection and Sobel edge detection algorithm are used to extract edges from facial images which is used to detect face. Performance factors are analyzed namely accuracy and speed are used to find out which algorithm works better. . From the experimental results, it is observed that the Canny edge detection algorithm works better than Sobel edge detection algorithms. Wang and Shuyuan [2005] have proposed a method that, Automatic edge detection of an image is considered a type of crucial information that can be extracted by applying detectors with different techniques. It is a main tool in pattern recognition, image segmentation, and scene analysis. This paper introduces an edge-detection algorithm, which generates multi-threshold values. It is based on non-Shannon measures such as Havrda & Charvat's entropy, which is commonly used in gray level image analysis in many types of images such as satellite grayscale images. The proposed edge detection performance is compared to the previous classic methods, such as Roberts, Prewitt, and Sobel methods. Numerical results underline the robustness of the presented approach. Maszczyk and Duch [2008] have proposed that, Shannon entropy used in standard top-down decision trees does not guarantee the best generalization. Split criteria based on generalized entropies offer different compromise between purity of nodes and overall information gain. The modified decision trees based on Tsallis and Renyi entropies have been tested on several high-dimensional microarray datasets with interesting results. This approach may be used in any decision tree and information selection algorithm. Svobod et al., have presented a paper for edge detection which utilizes a number of different statistical tests to analyze different properties across mask based regions within an image. The performance of this novel technique is objectively assessed against the traditional Canny filter using an adapted figure of merit calculation which works successfully on grey-scale images. This evaluation illustrates how the novel filter can outperform the more traditional edge detectors on images where texture is a more significant edge discriminator than intensity, namely in histological image data. Mohamed A. El-Sayed, have proposed an algorithm for edge detection in gray level images. The main objective of this paper is to solve the previous problem of traditional methods with generate suitable quality of edge detection. Their proposed algorithm is based on two definitions of entropy: Shannon's classical concept and a variation called Tsallis entropy. The effectiveness is demonstrated by using many different kinds of test images from the real-world and synthetic images. Panda and Patnaik, have presented a paper for edge dectection using Derivative Filters. proposed anew derivative filter of first order and described a novel approach of edge finding with an aim to find better edge map in a restored gray scale image. Subjective method has been used by visually comparing the performance of the proposed derivative filter with other existing first and second order derivative filters. The root mean square error and root mean square of signal to noise ratio have been used for objective evaluation of the derivative filters. Finally, to validate the efficiency of the filtering schemes different algorithms are proposed and the simulation study has been carried out using MATLAB 5.0. El-Sayed and Sennari [2014] have proposed a paper which introduces an edge-detection algorithm, which generates multi-threshold values. It is based on non-Shannon measures such as Havrda & Charvat's entropy, which is commonly used in gray level image analysis in many types of images such as satellite grayscale images. Ashour et al. [2014] have presented a paper which is based on different Multi-Threshold values using Shannon entropy to solve the problem of the traditional methods. It minimises the computation time. In addition to the high quality of output of edge image, another benefit comes from easy implementation of this method. Vijayarani and Vinupriya [2013] have provided a comparison between two edge detection algorithms namely Canny edge detection and Sobel edge detection algorithm for Extracting edges from facial images which is used to detect face. Performance factors are analyzed namely accuracy and speed are used to find out which algorithm works better. . From the experimental results, it is observed that the Canny edge detection algorithm works better than Sobel edge detection algorithms. Canny [1986] have proposed a paper which describes a computational approach to edge detection. The success of the approach depends on the definition of a comprehensive set of goals for the computation of edge points. These goals must be precise enough to delimit the desired behavior of the detector while making minimal assumptions about the form of the solution. We define detection and localization criteria for a class of edges, and present mathematical forms for these criteria as functionals on the operator impulse response. A third criterion is then added to ensure that the detector has only one response to- a single edge. Khan M.S.I. [2012] has presented a paper on using Canny edge detection algorithm for industrial image processing application for baked Goods. Images of baked objects on a conveyor belt are taken by high resolution cameras batch wise throughout the baking period. The network is designed with high performance equipment and the application is fast enough to complete all the steps within the allowed time window. The application uses Canny edge detection method [Shrivakshan G.T. and Chandrasekar C., 2012] which optimizes the performance compared to other applications used in the industry.

Through this paper, we have presented a simple approach for a comprehensive study of edge detection techniques in image processing applications using PSO and Renyi entropy to exhibit fairly improved performance in detection of image edge. The proposed algorithm is targeted for implementation in devices with low computation power and low memory foot print like microcontrollers and microprocessors.

## INFORMATION CONTENT IN IMAGE

In this section we outline various key background concepts that have formed the basis of the work presented in this paper.

### Information Content - Entropy

Entropy is used to measure the amount of information. Entropy is defined in terms of the probabilistic behaviour of a source of information. Let the events $e_1, e_2, \cdots, e_N$ are occurring with probabilities $p_1, p_2, \cdots, p_N$, N being the total number of states, where $\Sigma\, p_i = 1$, $i = 1,2,\ldots,N$ and $0 \leq p_i \leq 1$, $i \in [1,N]$ [El-Sayed M.A. and Khfagy M.A., 2011]. Entropy is simply the average (expected) amount of the information from the event.

### Shannon entropy

The growth of telecommunications in the early twentieth century led several researchers to study the information content of signals. Based on the work of Nyquist and Hartley, Shannon rationalized these early efforts into a coherent mathematical theory of communication and initiated the area of research now known as information theory [Bromiley P.A., et. al.]. Shannon states that a measure of the amount of information H(p) contained in a series of (rather a set of independent) events $P = \{p_1, p_2,\ldots,p_N\}$ should satisfy the following three requirements:

(i) H should be continuous in the $p_i$;

(ii) if all the $p_i$ are of equal probability, making $p_i = 1/N$, then H should be a monotonic increasing function of N;

(iii) H should be additive for independent sources

Then Shannon proved that the only H satisfying these three requirements is rep[resented by:

$$H(P) = -K\sum_{i=1}^{N} p_i \ln(p_i) \tag{1}$$

where K is a positive. This quantity is popularly defined as the Shannon entropy [El-Sayed M.A. and Khfagy M.A., 2011, Bromiley P.A., et. al.]. This has been used in a variety of applications: in particular, Shannon entropy is often stated to be the origin of the mutual information measure used in multi-modality medical image coregistration.

If we consider that a system can be decomposed in two statistical independent subsystems A and B, the Shannon entropy has the extensive property: S(A+B) = S(A)+ S(B). This formalism has been shown to be restricted to the Boltzmann-Gibbs-Shannon (BGS) statistics [Pattanaik A., et. al., 2015], [Singh B. and Singh A.P., 2008].

### Renyi's entropy

Extensions of hannon's original work have resulted in many alternative measures of information or entropy. For instance, by relaxing the third of Shannon's requirements, that of additivity, Renyi [Bromiley P.A., et. al., & Renyi A., 1961] was able to extend Shannon entropy to a continuous family of entropy measures that obey

$$H_\alpha(P) = \frac{1}{1-\alpha} \ln \sum_{i=1}^{N} p_i^\alpha \tag{2}$$

The Renyi entropy tends to Shannon entropy as $\alpha \to 1$.

In addition, Kendall defines the information content of a probability distribution [Bromiley P.A. et. al.] in the discrete case as:

$$I_\alpha(P) = \frac{1}{1-\alpha} - \sum_{i=1}^{N} \frac{p_i^\alpha}{\alpha - 1} \tag{3}$$

which again tends to the Shannon entropy as $\alpha \to 1$.

Selection of suitable threshold value

Let f(x, y) be the gray value of the pixel located at the point (x, y). In a digital image of size M×N, $1 \le x \le M$ and $1 \le y \le N$. Let the histogram be h(a) for $a \in G = \{0, 1, 2, \ldots, 255\}$ with f as the amplitude (brightness) of the image at the real coordinate position (x, y). Let t be a threshold value, the optimal threshold τ is determined by optimizing a suitable criterion function obtained from the gray level distribution of the image and some other features of the image. If τ is determined solely from the gray level of each pixel, the thresholding method is point dependent [El-Sayed M.A. and Khfagy M.A., 2011]. The result of thresholding an image function f(x, y) at gray level T is a binary function $f_T(x, y)$ such that $f_T(x, y) = 0$ if $f_T(x, y) \le T$ otherwise, $f_T(x, y) = 1$. In general, a thresholding method determines the value τ of T based on a certain criterion function. The Renyi entropy is a one-parameter generalization of the Shannon entropy. There is extensive literature on the applications of the Renyi entropy in many fields from biology, medicine, genetics, linguistics, and economics to electrical engineering, computer science, geophysics, chemistry and physics [El-Sayed M.A. and Khfagy M.A., 2011]. The Renyi's entropy measure of order α of an image, $H_\alpha(P)$ is as defined in equation (2) is given by:

$$H_\alpha(P) = \frac{1}{1-\alpha} \ln \sum_{i=0}^{255} (p_i)^\alpha \tag{4}$$

where $\alpha \neq 1$ is a positive real parameter. Since Shannon entropy measure is a special case of the Renyi entropy for $\alpha \to 1$.

Let $p_i = p_0, p_1, \ldots, p_N$ be the probability distribution for an image with N 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:

$$p_A : p_0/P_A, p_1/P_A, \ldots, p_t/P_A \quad \text{and}$$

$$p_B : p_{t+1}/P_B, p_{t+2}/P_B, \ldots, p_N/P_B \tag{5}$$

where $P_A = \sum_{i=0}^{t} p_i$ and $P_B = \sum_{i=t-1}^{N} p_i = 1 - P_A$.

For the gray levels G, put N = 255. The Renyi entropy of order α for each distribution is defined as:

$$H_\alpha^A(t) = \frac{1}{1-\alpha} \ln \sum_{i=0}^{t} (p_i / P_A)^\alpha \tag{6}$$

and

$$H_\alpha^B(t) = \frac{1}{1-\alpha} \ln \sum_{i=t+1}^{255} (p_i / P_B)^\alpha \tag{7}$$

$H_\alpha(t)$ is parametrically dependent upon the threshold value t for the foreground and background. We try to maximize the information measure between the two classes (object and background). When $H_\alpha(t)$ is maximized, the luminance level t that maximizes the function is considered to be the optimum threshold value τ

$$\tau(\alpha) = Arg \max_{t \in G} [H_\alpha^A(t) + H_\alpha^B(t)] \tag{8}$$

The technique consists of treating each pixel of the original image and creating a new image, such that $f_t(x, y) = 0$ if $f_t(x, y) \le \tau(\alpha)$ otherwise, $f_t(x, y) = 1$ for every $1 \le x \le M$ and $1 \le y \le N$. Since Shannon entropy measure is a special case of the Renyi entropy, the following expression can be used as a criterion function to obtain the optimal threshold at $\alpha \to 1$.

$$\tau(1) = Arg \max_{t \in G} [S^A(t) + S^B(t)] \tag{9}$$

To select suitable threshold value τ and α can now be described as follows in RenyiThreshold algorithm [5]:

**Algorithm RenyiThreshold:**

**Input:** A digital grayscale image $A$ of size $M \times N$.
**Output:** Threshold value τ at the parameter α.
**Begin**

1. Let $f(x, y)$ be the original gray value of the pixel at the point $(x, y)$, $x = 1..M$, $y = 1..N$.
2. For all $i = 0, 1, \ldots, 255$, calculate $p_i$ and $P$.
3. For all $t \in \{0, 1, \ldots, 255\}$:
   i. Calculate $P_A$, $P_B$, $p_A$ and $p_B$.
   ii. Calculate $H_\alpha^A(t)$ and $H_\alpha^B(t)$
   iii. For α>0, calculate $t^*(\alpha)$, using Equations (8, 9)

**End.**
**End algorithm.**

**Figure 1: ReniyuThreshold Algorithm**

## PARTICLE SWARM OPTIMIZATION (PSO)

PSO originally proposed by Kennedy and Eberhart [1995] is a novel evolutionary algorithm modelled after the flocking behaviour of birds. In PSO scheme, a swarm of birds (called particles) represents the solution space where each particle represents a candidate solution to the problem, characterised by its position vector **x** and velocity vector **v**. The quality or fitness of the solution that each particle implies is denoted by a function of its current position: f(**x**). Particles in PSO follow a very simple mechanism to evolve their behaviour: by trying to match the success of neighbouring particles and their own success achieved. Considering each particle of dimension n and the swarm of size Np, the position and velocity of the $i^{th}$ particle in the swarm, $i \in [1,Np]$, at the $t^{th}$ generation can be represented as: $\mathbf{x}_i^t = (x_{i1}^t, x_{i2}^t, ..., x_{in}^t)$ and $\mathbf{v}_i^t = (v_{i1}^t, v_{i2}^t, ..., v_{in}^t)$ respectively. Mathematically, the new position and velocity of each bird is represented as:

$$\mathbf{v}_i^{t+1} = \omega \mathbf{v}_i^t + c_1 r_1 (\mathbf{p}_i^t - \mathbf{x}_i^t) + c_2 r_2 (\mathbf{g}^t - \mathbf{x}_i^t), \quad (1)$$

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \mathbf{v}_i^{t+1} \quad (2)$$

where $r_1, r_2 \in [0,1]$ are uniform random numbers, ω is the inertia weight that controls the fluidity of the medium in which the bird moves, $c_1$ and $c_2$ are the positive acceleration coefficients that controls the convergence by driving the particle towards the local and global best solutions, respectively; $\mathbf{v}^t$ and $\mathbf{x}^t$ are the velocity and position of the particle at $t^{th}$ iteration; p and g are respectively the particle's personal and global best position attended so far. The rule for updating p of $i^{th}$ particle in $t^{th}$ iteration is as follows:

$$\mathbf{p}_i^t = \begin{cases} \mathbf{p}_i^{t-1} & \mathit{if}\, f(\mathbf{x}_i^t) > f(\mathbf{p}_i^t) \\ \mathbf{x}_i^t, & \mathit{otherwise} \end{cases} \quad (3)$$

The value of g of the swarm in $t^{th}$ iteration is obtained as:

$$\mathbf{g}^t = \begin{cases} \min f(\mathbf{p}_i^t)\big|_{i=1}^{NP} & \text{if } \min f(\mathbf{p}_i^t) \le f(\mathbf{g}^{t-1}) \\ \mathbf{g}^{t-1}, & \text{otherwise} \end{cases} \quad (4)$$

The pseudo code algorithm and the flowchart of the PSO as an aid to understanding functioning of the algorithm is given below in Fig. 2 and Fig. 3, respectively:

```
BEGIN
  INITIALIZE parameters;
  FOR each particle
    INITIALIZE particle position and particle velocity;
  END
  DO
    FOR each particle
      CALCULATE fitness value;
      IF (the fitness value is better than
        the best fitness value (pBest) in history)
        set current value as the new pBest;
    END
    SELECT the particle with the best fitness value
                  of all the particles as the gBest;
    FOR each particle
      CALCULATE particle velocity;
      UPDATE particle position;
    END
  WHILE (TERMINATION CONDITION not satisfied)
END
```

**Figure 2: Pseudo Code Algorithm for the PSO**

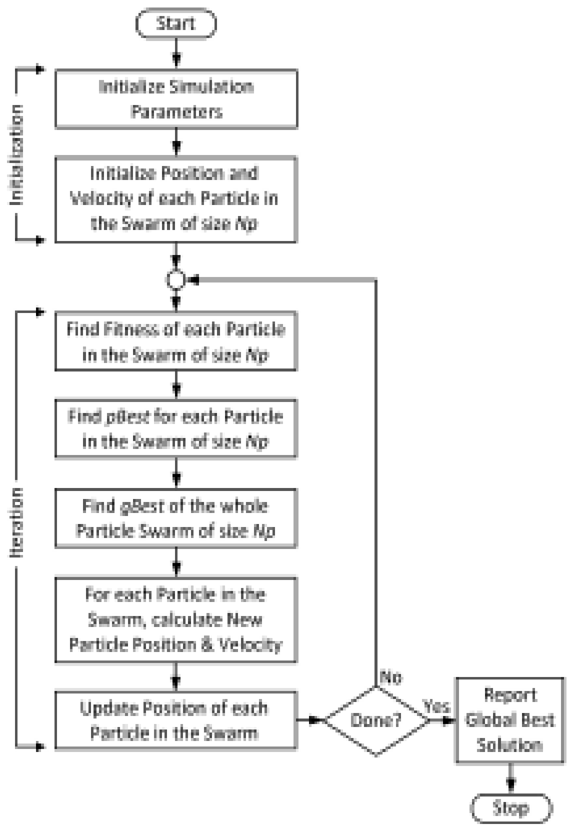



**Figure 3: Flowchart for the PSO**

## RESULTS ANALYSIS

In this section, the experimental results for reflecting the comprehensive study of edge detection techniques in image processing applications using PSO are presented. The performance of the proposed scheme is evaluated through the simulation results using MATLAB for a many test images. The implementation of the proposed algorithm is done in MATLAB 7.8 using a computer with Intel i3 Processor (2.20GHz) and 4 GB RAM.

For the purpose of simulation based study, standard test images were taken from online image databases provided by Berkley Segmentation Database (BSD300) [Berkeley image database]. Here, we are present a set of only four test images and the results of the Renyi entropy are compared with the results of well-established optimization algorithm (PSO) on the same set of test images. PSO method is chosen for comparison because for it's simple structure, ease of use, and it's speed and robustness. Our analysis is based on how much information is lost due to thresholding. In this analysis, given two threshold images of a same original image, we prefer the one which lost the least amount of information. The optimal threshold value was computed by the proposed method for these images. Table 5 lists the optimal threshold values that are found for these images for α values equal to 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9 and 0.95, respectively. The original images together with their histograms and the thresholded images obtained by using the optimal threshold of some values t*. Using the above images, we conclude that when α value lies between 0 and 1, our proposed method produced good optimal threshold values.

**(a) Hoarding**


**(b) Landscape**


**(c) Golf**


**(d) Desert**

**Figure 4: BSD300 Standard Text Images**

Results of simulation are presented in the following tables. Headings of the data presented in the table are self-explanatory.

**Table 1: Optimal Threshold Value Using Renyi Entropy**

| Image | Threshold Value α | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
| Hoarding | 124 | 121 | 118 | 115 | 113 | 112 | 110 | 109 | 108 | 107 |
| Landscape | 135 | 134 | 130 | 123 | 119 | 117 | 116 | 114 | 113 | 113 |
| Golf | 135 | 134 | 132 | 117 | 114 | 113 | 112 | 111 | 111 | 110 |
| Desert | 141 | 140 | 140 | 140 | 141 | 141 | 141 | 141 | 141 | 141 |

**Table 2: Classification Accuracy using Renyi Entropy**

| Image | Threshold Value α | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
| Hoarding | 0.8902 | **0.8909** | 0.8907 | 0.8887 | 0.8866 | 0.8845 | 0.8799 | 0.8775 | 0.8743 | 0.8701 |
| Landscape | **0.9188** | 0.9160 | 0.9067 | 0.9055 | 0.9054 | 0.9042 | 0.9040 | 0.9032 | 0.9031 | 0.9031 |
| Golf | **0.9009** | 0.8982 | 0.8915 | 0.8681 | 0.8811 | 0.8842 | 0.8808 | 0.8886 | 0.8886 | 0.8900 |
| Desert | 0.9090 | **0.9104** | **0.9104** | **0.9104** | 0.9090 | 0.9090 | 0.9090 | 0.9090 | 0.9090 | 0.9090 |

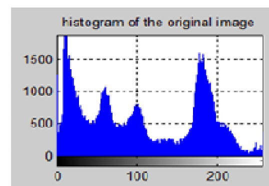
**Table 3: Optimal Thresholding Using PSO Algorithm**

| Image | Threshold Value α | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
| Hoarding | 124 | **121** | 118 | 115 | 113 | 112 | 110 | 109 | 108 | 107 |
| Landscape | **135** | 134 | 130 | 123 | 119 | 117 | 116 | 114 | 113 | 113 |
| Golf | **135** | 134 | 132 | 117 | 114 | 113 | 112 | 111 | 111 | 110 |
| Desert | 141 | **140** | **140** | **140** | 141 | 141 | 141 | 141 | 141 | 141 |

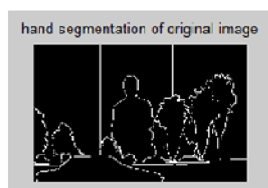
**Table 4: Classification Accuracy Using PSO Algorithm**

| Image | Threshold Value α | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 0.95 |
| Hoarding | 0.8902 | **0.8908** | 0.8907 | 0.8887 | 0.8865 | 0.8844 | 0.8799 | 0.8774 | 0.8742 | 0.8701 |
| Landscape | **0.9188** | 0.9159 | 0.9067 | 0.9054 | 0.9053 | 0.9042 | 0.9040 | 0.9032 | 0.9031 | 0.9031 |
| Golf | **0.9008** | 0.8981 | 0.8915 | 0.8880 | 0.8811 | 0.8842 | .8868 | 0.8885 | 0.8865 | 0.8899 |
| Desert | 0.9090 | **0.9104** | **0.9104** | **0.9104** | 0.9090 | 0.9090 | 0.9090 | 0.9090 | 0.9090 | 0.9090 |

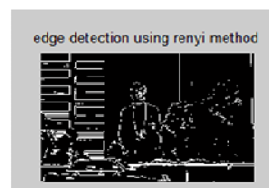
**(a)**




**(b)**

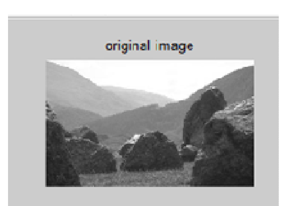



**(c)**

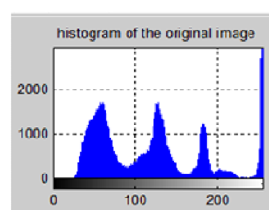



**(d)**

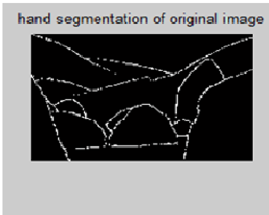
**Figure 5: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using Renyi method α = 0.9, τ = 109**



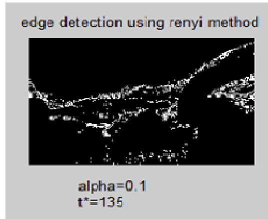

**(a)**




**(b)**

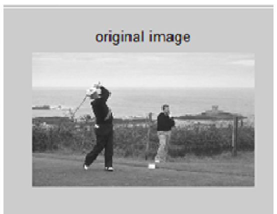



(c)

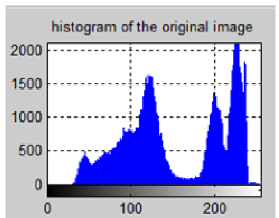



(d)

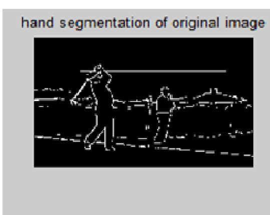
**Figure 6: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using Renyi method α = 0.1, τ = 135**



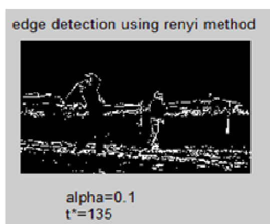

(a)




(b)



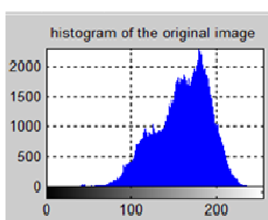

(c)



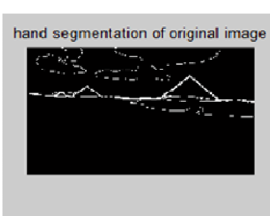

(d)

**Figure 7: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using Renyi method α = 0.1, τ = 135**

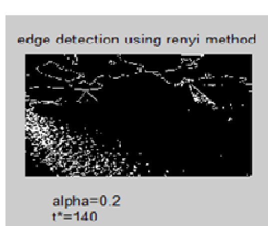

(a)




(b)



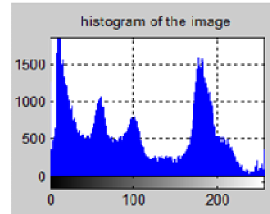

(c)



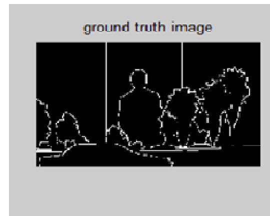

(d)

**Figure 8: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using Renyi method α = 0.2, τ = 140**

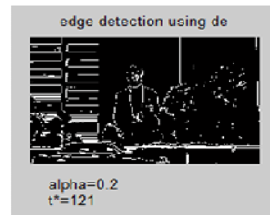

(a)




(b)



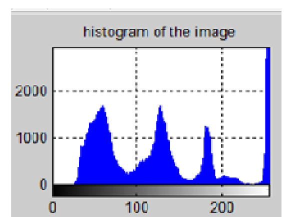

(c)



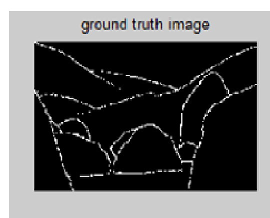

(d)

**Figure 9: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using PSO method α = 0.2, τ = 121**

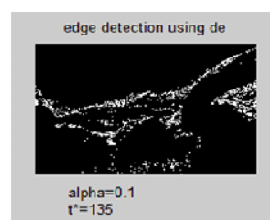

(a)




(b)

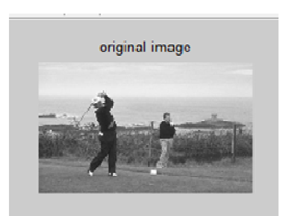



(c)

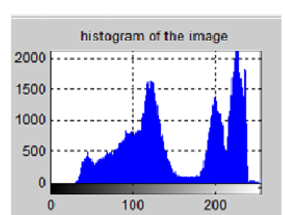



(d)

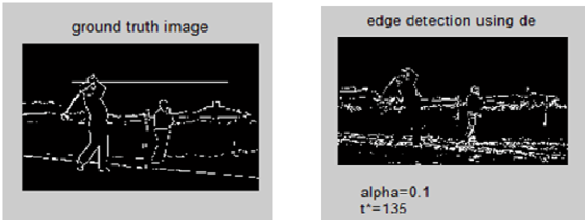
**Figure 10: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using PSO method α = 0.1, τ = 135**




(a)

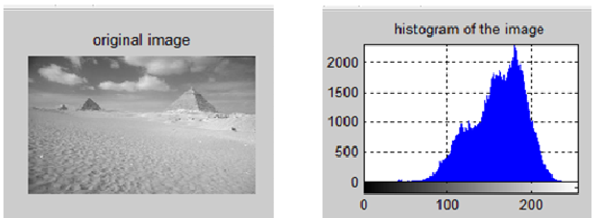



(b)

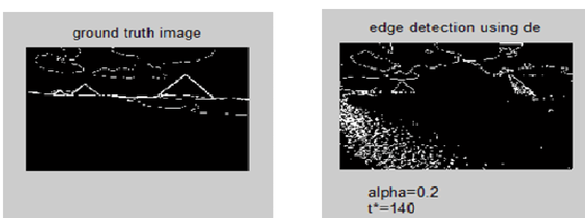



(c) (d)

**Figure 11: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using PSO method α = 0.1, τ = 135**




(a) (b)




(c) (d)

**Figure 12: (a) Original Image, (b) histogram of image, (c) ground truth image, and (d) edge detection using PSO method α = 0.2, τ = 140**

## CONCLUSION

The main objective of this work is to study and understand the process of edge detection in natural and synthetic images. An entropy based approach was chosen to perform the image edge detection task. In this regard the well-known Renyi entropy has been used for the application in hand. The Renyi entropy has been used for the task of automatic thresholding. The entropy was calculated from the 1-dimensional histogram of the images. The following strengths with the Renyi entropy metrics were readily defined: Numerically robust, computationally fast and Easy to implement. For effective thresholding the Renyi entropy must become maximum at the threshold point. Thus this problem of finding maximum of Renyi entropy can be posed as an optimization problem.

In this paper PSO is used to find out the optimized value of the threshold. To measure the effectiveness of the thresholding and edge detection process, CA has been used. The result justify that the Renyi entropy can be used as a means for automatic thresholding and edge detection of image. The combination of Renyi entropy and PSO can be used effectively for the edge detection application. The order α can be used as an adjustable value and can play an important role as a tuning parameter of the image detection chain for the same class of images.

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