Optimized Histogram Equalization

for

Image Enhancement

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Thesis submitted in partial fulfilment

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by

M Bhubaneswari

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under the supervision of

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Dr. Banshidhar Majhi
Professor

May, 2015

Certificate

This is to certify that the work in the thesis entitled ***Optimized Histogram Equalization for Image Enhancement*** by ***M Bhubaneswari***,bearing roll no ***111cs0063*** is a record of an original work carried out with my supervision and guidance in partial fulfilment of the requirements for the degree of Bachelor in Technology in Computer Science and Engineering. Neither this thesis nor any part of it has been submitted for any degree elsewhere.

Banshidhar Majhi
Professor
Department of CSE, NIT Rourkela

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First and foremost, I would like to express my deepest gratitude to my supervisor Prof. B. Majhi for introducing me to this exciting area of Optimization Algorithms . Even out of his busy schedule , he would always manage to help me with the smallest of doubts . I will remain indebted to him for his guidance, support and patience with me throughout the course of my research. It is due to his faith in me that today I am submitting this thesis. It has been my privilege working with him and learning from him.

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M Bhubaneswari

Abstract

In this project, Image Enhancement has been achieved by performing Histogram Equalization that uses optimization algorithms to optimize parameters.Histogram equalization is a spatial domain image enhancement technique, which effectively enhances the contrast of an image.However, while it takes care of contrast enhancement,it does not consider the abrupt changes in the image brightness due to which image brightness is not preserved.Hence,in this project a modified histogram equalization technique using optimization algorithm has been proposed, which takes care of contrast enhancement while ensuring brightness preservation.The idea used here is to first ,section the data image histogram into two, utilizing otsu's limit .Then an arrangement of streamlined measuring requirements are formed and connected on both the sub-images. Then, the sub-images are evened out freely and their union creates the contrast enhanced , brightness preserved output image .Here we have used three Optimization Algorithms for finding the optimal constraints . First , Genetic Algorithm(GA) has been used , to optimise the constraints .Second , Particle Swarm Optimization (PSO) has been used and third ,a Hybrid PSO Optimization Algorithm has been used for the same .Then the results produced by the above algorithms are compared to find out which one outperforms the other , by comparing various parameters like Discrete Entropy , Mean , Number of Generations.

***K*eywords** : Image enhancement , Histogram equalization ,Genetic Algorithm, Particle swarm optimization , Hybrid PSO , Otsus threshold , Discrete Entropy ,Mean, Generation.

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Chapter 1

Introduction

Picture Enhancement alludes to a procedure of preparing pictures to bring out particular highlights of a picture . It's standard target is to highlights certain key attributes of a picture and to process the picture so that the outcome is more suitable than the first picture for a particular application . It emphasizes and hones the picture highlights, for example, edges, limits or difference to make a realistic show more supportive for showcase and examination. The upgrade does not enhance the intrinsic data substance of the information, however it expands the dynamic scope of the particular highlights with the goal that they can be identified and broke down effortlessly. The best trouble in picture improvement is evaluating the rule for upgrade and, henceforth, an extensive number of picture improvement strategies are observational and require intelligent methods to get agreeable results.

1.1 Contrast Enhancement

Especially for this Project, our goal is to improve the picture differentiation while saving the shine of the image.Various contrast upgrade procedures are utilized as a part of picture and feature transforming for attaining to better visual standpoint. Histogram leveling based systems means to achieve contrast upgrade by redistributing the power estimations of an info picture, in this way straightening the histogram. Histogram change is a profoundly utilized method as a part of a hefty portion of the complexity upgrade techniques.In general, Histogram Equalization (HE) is a standout amongst the most favored methods to attain to difference improvement, because of its adequacy and straightforwardness. HE based upgrade discovers significant applications in medicinal picture preparing, surface union, discourse acknowledgment, satellite picture transforming, and so on.

HE routines can be partitioned into two general classifications in particular Global and neighborhood. Global histogram Equalization strategies enhance the picture nature of by normalizing the force dispersion over its dynamic reach, by utilizing the histogram of the whole data picture. It is accomplished by the control of the force conveyance by the utilization its Cumulative Density Function(CDF), along these lines accomplishing a resultant picture with direct dispersion of intensities . HE generously alters the mean estimation of the first picture ,in this manner presenting a washed-out impact in the yield picture .

Local Histogram Equalization(LHE) strategy considers the histogram power measurements of its neighborhood pixels of a picture for performing standardization. These systems work by separating the first picture into different non-covering sub-pieces and performs exclusively performs histogram evening out every sub-squares. The consolidating the sub-pieces utilizing the bilinear addition strategy delivers the resultant image.But this technique accompanies an escape clause for presenting checker board impact close to the limits of the sub-obstructs .There is this another upgrade method in particular, Histogram Specification (HS),in which a coveted yield histogram is determined to control the normal output.However, it is a monotonous assignment to indicate the yield histogram design as it shifts with the pictures.

In this project ,A optimized Histogram Equalization has been implemented using Otsu's method to perform thresholding.Then these sub-histograms are manipulated by a set of weighing constraints, before being equalized independently .The set of weighing constraints are then optimized using Genetic Algorithm(GA), Particle Swarm Optimization(PSO) and a Hybrid GA-PSO algorithm ,which are population-based optimization technique . The results produced on using both the algorithms to optimize the constraints are compared to find out which one outperforms the other , by comparing their Entropy,Mean and number of generations .

1.2 Thesis Organization

The rest of the thesis include the following chapters:

Chapter 2: **Literature Review**

Includes a literature review on the conventional Histogram equalization and a few recently proposed HE based methods are described .

Chapter 3: **Optimization Algorithms**

Shows the details of various Optimization Algorithms.

Chapter 4: **Optimized Histogram Equalization**

Elaborates the working principle of the proposed technique and various aspects of the Contrast enhancement.

Chapter 5:**Conclusion and Future Work**

The conclusion is given and future work has been discussed.

Chapter 2

Literature review

The ordinary histogram leveling procedure has been depicted beneath . For a given data input, *F(i, j)*having n number of pixels in the gray range $[X_0, X_{n-1}]$.For the level r_k, the Probability Density Function(PDF), $P(r_k)$is given by

$$p(r_k) = n_k/n$$

Where, n_k portrays the recurrence of event of the level r_k in the information picture ,n speaks to the aggregate number of pixels in the picture and $k = 0, 1, 2..., N-1$.A plot of n_k against r_k issues us the histogram of the picture F.Thus, the cumulative density function(CDF) can be ascertained as :

$$C(r_k) = \sum_{i=1}^{k} p(r_i)$$

HE maps an image into the whole element range,$[X_0, X_{n-1}]$ utilizing the comparison which is given as :

$$f(X) = X_0 + (X_{n-1} - X_0) * C(X)$$

Kim et al. proposed a modified HE technique called as Brightness Preserving Bi-Histogram Equalization(BBHE)[10] in the year 1997. BBHE considers the mean of the image for segmenting the histogram of the input image into two parts.The first one containing pixel values less that the mean and the other ranging from mean to the maximum pixel value.It then independently normalizes the two histograms and their union produces a resultant image with brightness preserved.

Another variation of HE was proposed by Wan et al. in 1999 called equal area Dualistic Sub-Image Histogram Equalization (DSIHE)[11] which is an improved version of BBHE .It's only the segmentation process that differentiates DSIHE from BBHE.In case of DSIHE,median is considered for segmenting the input image into two parts. Images with irregular intensity distribution are best suited for this method. But, The brightness preserving ability of this method is not found to be impressive.

Another expansion of BBHE, called Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE)[12] was proposed by Chen and Ramli in 2001.MMBEBHE fragments the histogram in view of the limit value,such that the contrast in the middle of data and yield mean, called Absolute Mean Brightness Error (AMBE), is minimum.This method additionally accompanies neglected impacts.

Chen and Ramli proposed a Recursive Mean Separate Histogram Equalization (RMSHE) method in 2003.This system meets expectations by recursively parceling the histogram of the given picture and afterward autonomously leveling every segment.The union of every last one of fragments yields the difference upgraded picture. This technique has been demonstrated to have a hand over the recursive parceling methodologies

Another strategy that is very like the RMSHE, called Recursive Sub-Image Histogram Equalization(RSIHE) was proposed for a comparable system by sim et al. in 2007 .This system chips away at the dim level with CDF equivalent to 0.5 for differentiating the histogram, rather than the mean seperation methodology utilized by RMSHE. This strategy has ended up being superior to RMSHE.However, the computational unpredictability increments because of recursive nature delivering a yield picture very like the first image,as the recursion level increments.

A successful and quick system known as Weighted Thresholded Histogram Equalization(WTHE) was proposed in 2007 for picture and feature contrast improvement. This method gives a productive system to controlling the procedure of improvement .WTHE strategy accompanies two-fold advantages such as,adaptivity to distinctive pictures and simplicity of control,which is very hard to accomplish in the Global HE-based upgrade systems.

Chapter 3

Optimization Algorithms

In computer science and mathematics, an optimization problem solves the problem of finding the best solution from the solutions space.Based on the convergence aspect, Optimization algorithms can be categorised under Local Optimization and Global Optimization.Local Optimization algorithm converge on the local best whereas Global converges on the overall best skipping all the local ones. Optimization problems can also be categorised depending on the type of variables ie. continuous or discrete. Combinatorial optimization works on discrete variables.

The standard form of a continuous optimization problem is :

Minimize/Maximize $f(x)$

where $f(x) : R^n \rightarrow R$ is the objective function to be minimized over the variable x.

The two types of optimization are Local Optimization and Global Optimization.

Local Minimization gives the smallest value the function can attain in some feasible neighbourhood

Local minimum $f^* = f(x^*)$,with local minimizer x^* such that $x^* \varepsilon \delta$
there exists a $\delta > 0$ such that $f^* <= f(x)$ for all x in $x \varepsilon \delta : |x - x^*| <= \delta$.

Global Minimization gives the smallest function value over all the solution space.

Global minimum $f^* = f(x^*)$,with local minimizer x^*

$f^* <= f(x)$ for all $x \varepsilon \delta$

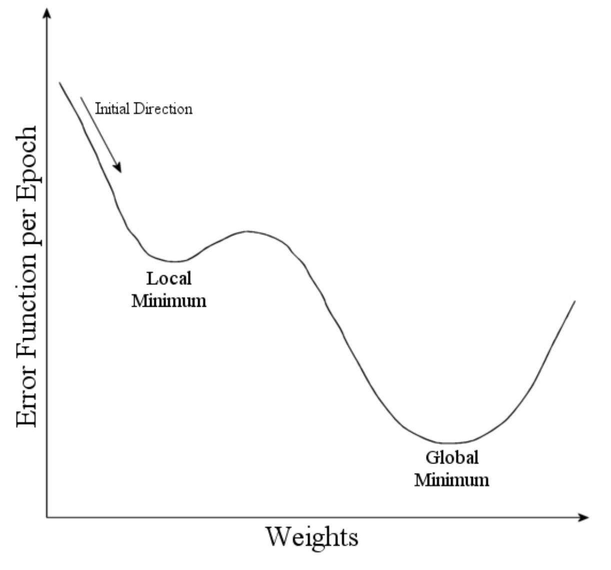


Figure 3.1: Local and global minima for a specific function

3.1 Genetic Algorithm

Genetic Algorithm belongs to the class of evolutionary, search heuristic algorithm based on the ideas of genetics and natural selection.It falls under the class Evolutionary computing[9] ,which is a immensely growing area of artificial intelligence . GAs derives its inspiration from Darwins theory of evolution survival of the fittest. GA's use smart operators to tackle improvement issues .Even however randomized in its activity, GA abuses crucial data to streamline the inquiry into the area where a superior execution can be normal inside the pursuit space.

3.1.1 Genetic Algorithm Operators

GA induces genetic diversity in every generation to keep alive the evolutionary process.GA accomplishes this task by the help of various Genetic Operators.Basically, the use of such operators are to ensure genetic diversification.The genetic operators find a sheer resemblence with the steps of evolution that occur in the real world.The various GA operators include:

- Selection
- Crossover
- Mutation

SELECTION :

We begin by initializing a random population of individuals and calculating there fitness values based on which we rank the individuals.This is where the Selection operator comes to play. Selection refers to extracting a attributes of genes from the present population ,based on measurable parameter ie. Fitness Value.Thus based on the fitness value we choose parents whose crossover will have maximum contribution in producing better offsprings. The most regularly utilized routines for selecting chromosome for mating :

- Roulette wheel selection
- Tounament selection

Roulette wheel selection : The basic theory is "fit parents produce fitter offsprings". So we calculate the fitness values of individuals and ranks them accordingly.Then depending on the fitness values,sections are assigned to the roulette wheel such that fitter solution gets bigger section.The roulette wheel n no of times , where n is the population size.Hence the fitter solution has higher chance of getting selected .

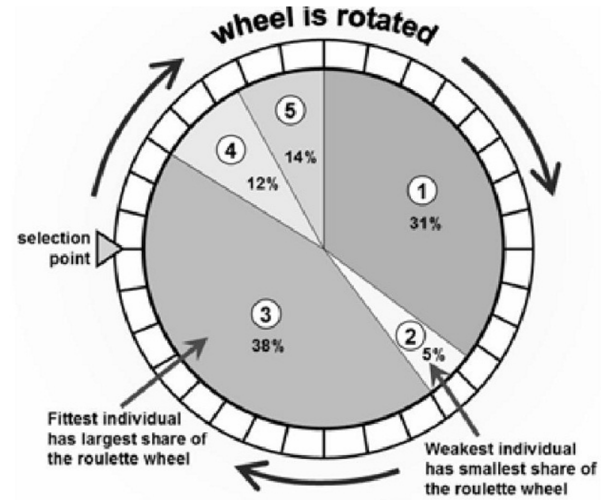
The table below lists a sample population of population size 5. Each individual consist of 10 bit chromosomes and are being used to optimise a simple mathematical function .

We can see from the table that individual No. 3 is the fittest individual and No. 2 is the weakest. This gives the strongest individual a value of 38% and the weakest 5%.

No.	Chromosome	$Value_{10}$	X	Fitness $f(x)$	% of Total
1	0001101011	107	1.05	6.82	31
2	1111011000	984	9.62	1.11	5
3	0100000101	261	2.55	8.48	38
4	1110100000	928	9.07	2.57	12
5	1110001011	907	8.87	3.08	14
Totals				22.05	100

Example population of 5 for: $f(x) = -\frac{1}{4}x^2 + 2x + 5$

(a) Table depicting probability distribution for Roulette wheel selection



(b) Roulette wheel for parent selection

Figure 3.2: Roulette wheel selection

CROSSOVER:

Crossover is a hereditary administrator that joins two prudently picked chromosomes to create posterity. The idea behind crossover is,to derive the best characteristics of both parents so that the new chromosome is better than both.A user defined value of crossover probability controls the extent of intermixing of genes. The various types of crossover operators are :

- One-point crossover
- Multi-point crossover
- Uniform crossover

Single Point Crossover : A crossover point is chosen randomly and then everything before this point from the first parent and then everything after the crossover point copy from the second parent is copied.

Parent 1 **1 1 : 0 1 0 1 0 0**

Parent 2 **1 0 : 0 0 1 1 1 0**

if the position 2 is chosen to be the cross over point , the resulting offsprings will be :

Offspring 1 **1 1 0 0 1 1 1 0**

Offspring 2 **1 1 0 1 0 1 0 0**

MUTATION :

Transformation is a hereditary administrator used to ensure hereditary traits are passed from one era of a population of chromosomes to the next. Transformation finds place amid population improvement as per a client perceptible changes. Mutation modifies one or more quality attribute in a chromosome from its introductory state. This altogether,gives rise to new qualities that are added to the quality pool. With the new quality values, the hereditary calculation may have the capacity to land at preferable arrangement over was beforehand possible.Change is an essential piece of the hereditary inquiry, serves to keep the populace from stagnating at any neighbourhood optima. The Mutation administrators are of numerous sorts:

- Flip bit
- Uniform

3.1.2 Genetic Algorithm

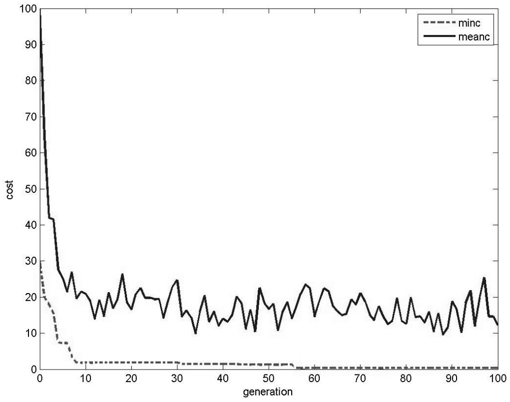
Algorithm 1 Genetic Algorithm

Require: An objective function $f(x, y)$.

1: [Start]Generate an initial Random Population of N chromosomes.
2: [Fitness]Evaluate the fitness values $f(x, y)$ for each particle in the population.
3: **for** $iter \leq maxiter$ **do**
4:     [Selection] Select fitter parent chromosomes from the population.
5:     [Crossover] With a crossover probability, mating is performed on the parent chromosomes so as to form fitter offsprings.
6:     [Mutation] With a mutation probablity ,mutate new offspring for diversified population.
7:     [Accepting]Place newly generated offsprings in the new population.
8:     [Replace]Use the new population to recompute the fitness values.
9:     Increment *iter* for the next generation.
10: **end for**
11: [Test]If stopping criteria is satisfied, the best solution in current population is retuned.
12: [Loop]Else Go to Step 2

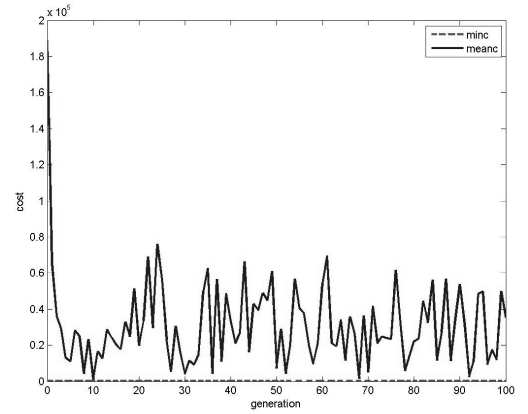
3.1.3 Genetic Algorithm Results

The plot showing convergence to global minima of a few standard functions is shown below:



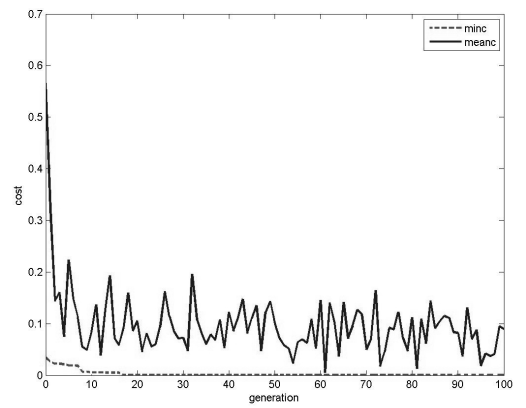
(a) Rastrigen Function

$f(x) = 10d + \sum_{i=1}^{d}(x_i^2 - 10cos(2\Pi x_i))$



(b) Rosenbrock Function

$f(x, y) = (1 - x)^2 + 100(y - x^2)^2$



(c) Grienwank Function $f(x) = \sum_{i=1}^{d}(\frac{x_i^2}{4000}) - \prod_{i=1}^{d}(cos(\frac{x_i}{\sqrt{i}})) + 1$

Figure 3.3: GA results for standard functions

3.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO), initially developed by Kennedy & Eberhart, is one of the enhancement systems impacted by the swarm knowledge for tackling improvement issues. PSO operations are taking into account the subjective connection and correspondence between individuals of the populace, for example, bird flocking together and fish schooling. This algorithm is quite easy to implement with very low computational expense, since its resource(memory and CPU speed)[4] requirements are low and unlike GA it does not have any operators .

PSO offers numerous purposes of likenesses with GA. Practically equivalent to GA,it additionally performs seeking utilizing a populace of people. Both the routines launch with a haphazardly produced population.In Swarm insight calculations, data contained by every individual in the populace is imparted among the rest, in this way creating a data pool.Each molecule can then determine its obliged data for its own particular benefit.Because PSO fits in with the class of swarm knowledge, it additionally works by the imparting of the individual best positions of every molecule in the population.Now that every molecule knows all the positions, a best molecule is picked and subsequently every molecule at the same time continues towards its close to home best and the best molecule of the swarm. Contrasted with GA, the PSO has some noteworthy qualities. It has memory, henceforth learning of the best arrangements is held by all the particles in the populace, while incase of GA, past data is decimated once the populace changes.

PSO constructs particle developments with respect to social cooperations, which controls the directions of a gathering free particles.The fitness estimations of every individual relies on upon its position, x_i.With each emphasis particles change their position, and therefore investigates more parts of the arrangement space, just by changing its related speed given by v_i. Truth be told, the primary PSO administrator is the speed redesign, that records the best position, regarding fitness estimation of every last one of particles amid their ways, p_g^t , and the individual best position that a individual spans amid its pursuit, p_i^t , bringing about a development of the whole swarm drawing closer the worldwide optimum.Velocity controls the coordinated development of the molecule while, position gives the measure of separation moved. At that point the speed and position of the particles are stochastically upgraded by :

$$v_i^{t+1} = w * v_i^t + C_1 * r_1^t * (p_i^t - x_i^t) + C_2 * r_2^t * (p_g^t - x_i^t)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

v_i^t represents particles velocity vector generation t,

x_i^t represents particles position vector generation t,

r_1 and r_2 represent random numbers in the range [0,1] ,

p_i denotes the best ever particle i ever took,

p_g corresponds to the global best position in the swarm up to iteration t ,

C_1 and C_2 depict the "trust" parameters demonstrating the amount of certainty the present molecule has in itself (C_1 or subjective parameter) and the amount of certainty it has in the swarm (C_2 or social parameter),w is the inertia weight[**?**]

3.2.1 PSO Algorithm

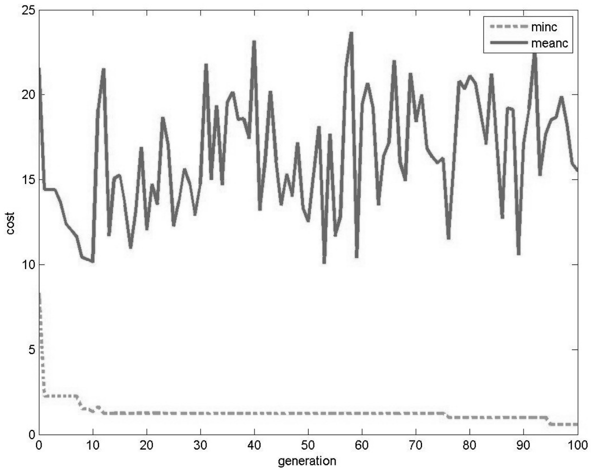
Algorithm 2 PSO Algorithm

Require: An objective function $f(x, y)$.

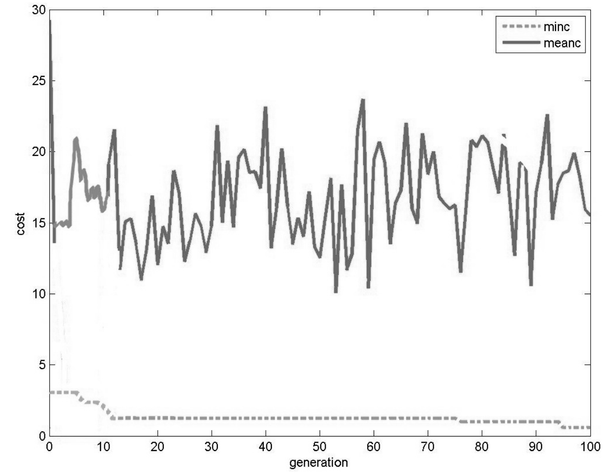
for each particle in the population **do**
    Initialize to a random value.
end for
for $iter \leq maxiter$ **do**
    for each particle in the population **do**
        Assess the fitness value.
        if Fitness value is superior to the best wellness value(pBest) in history **then**
            Set current value as the new pBest.
        end if
    end for
    pick the individual with the best wellness estimation of every last one of particles as the gBest. .
    for each particle in the population **do**
        Ascertain particle velocity as: $v_i^{t+1} = w * v_i^t + C_1 * r_1^t * (p_i^t - x_i^t) + C_2 * r_2^t * (p_g^t - x_i^t)$
        Update particle position as: $x_i^{t+1} = x_i^t + v_i^{t+1}$
    end for
    Increment $iter$ for the next generation.
end for

3.2.2 PSO Results

The plot showing convergence to global minima of a few standard functions is shown below:



(a) Rastrigen Function
$f(x) = 10d + \sum_{i=1}^{d}(x_i^2 - 10cos(2\Pi x_i))$



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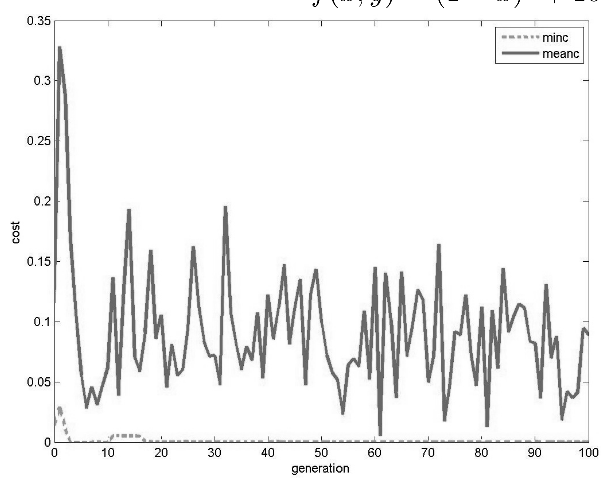


(c) Grienwank Function $f(x) = \sum_{i=1}^{d}(\frac{x_i^2}{4000}) - \prod_{i=1}^{d}(cos(\frac{x_i}{\sqrt{i}})) + 1$

Figure 3.4: PSO results for standard functions

3.3 Hybrid GA PSO Algorithm

A hybrid GA-PSO, is a population based optimization algorithm[**?**] that overcomes the demerits of PSO such as premature convergence.This Hybrid algorithm is achieved by integrating the PSO operations along with the fundamental techniques like selection ,crossover,mutation of GA. The main goal as we see is to harness the strong points of the algorithm in order is to keep a balance in between the exploration and exploitation . Combining search abilities of both the algorithms into one single algorithm, seems to be a logical approach.

3.3.1 Hybridization Approaches

PSO-GA (Type 1): Start the calculation with the first calculation and afterward apply the other system on the last populace acquired by the first method.For case, GA is connected on the populace for first a large portion of the cycles and the arrangements turn into the introductory populace of PSO. Remaining cycles are then run by PSO.

PSO-GA (Type 2): Coordinate the novel propperties of a specific strategy with the other technique.For illustration choice transformation and hybrid administrators of GA can be utilized as a part of PSO .This helps the stagnated pbest particles to change their positions by change administrator of GA which affects broadening[4].

3.3.2 Hybrid Algorithm operators

For the project, the Type-2 approach[5] has been implemented.The operators help acheiving the objectives of the hybrid algorithm. The algorithm consists of four major operators :

Enhancement:After computing the wellness estimations of every last one of people in the populace for every generartion, the top half best performing ones are checked as elites.Instead of repeating the elites specifically to the following generation,we upgrade them.Now the upgraded elites as folks produce offsprings that attain to preferable execution over the offsprings of the first elites.

Selection:Now once,the enhanced elite is obtained, we then use the GA operators on it.for the selection process,parents are selected based on a selection mechanism.Thus the selected parents create a mating pool.

Crossover:From the mating pool parents are selected randomly in pairs.They then undergo crossover operation to produce a pair of off-springs with better fitness values.

Mutation:The final Genetic operator is Mutation.It mutates the present population to generate a new population so as to maintain diversity.Now this step is purely optional, but its use produces better results.

3.3.3 Hybrid Algorithm

Algorithm 3 Hybrid GA PSO Algorithm

Require: An objective function $f(x, y)$.

1: Initialize a random population of a predefined population size.
2: calculate fitness for each particle and rank them accordingly.
3: **for** $iter \leq maxiter$ **do**
4: Apply PSO operators to the best half(elite) of the population by updating position and velocity vector as:
5: $v_i^{t+1} = w * v_i^t + C_1 * r_1^t * (p_i^t - x_i^t) + C_2 * r_2^t * (p_g^t - x_i^t)$
6: $x_i^{t+1} = x_i^t + v_i^{t+1}$
7: Selection operator is used to select parents from the PSO generated population.
8: Crossover is done on the selected parents from the mating pool to produce fitter offsprings.
9: Mutation with a predefined probability is applied to the updated population to induce diversification.
10: Update the population with the newly generated individuals.
11: Evaluate the fitness of the newly generated population.
12: Increment *iter* for the next generation.
13: **end for**

v_i^t is the velocity vector of particle i at iteration t,

x_i^t is the position vector of particle i at iteration t,

r_1 and r_2 represent random numbers in the range [0,1] ,

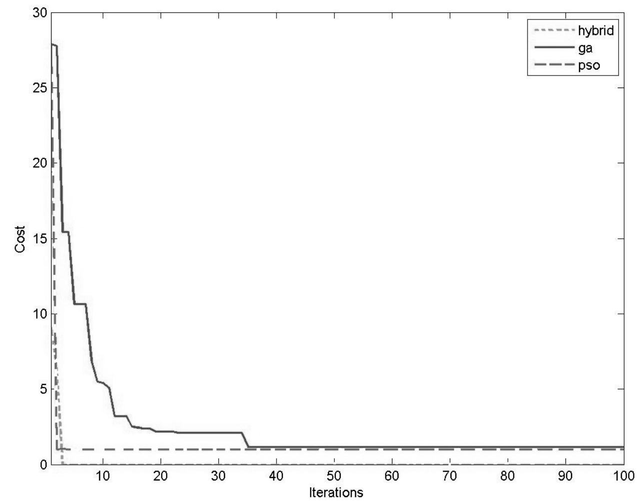
p_i denotes the best ever particle i ever took,

p_g corresponds to the global best position in the swarm up to iteration t ,

C_1 and C_2 depict the "trust" parameters demonstrating the amount of certainty the present molecule has in itself (C_1 or subjective parameter) and the amount of certainty it has in the swarm (C_2 or social parameter),w is the inertia weight[**?**].

3.3.4 Hybrid GA PSO results

The plot shows a comparison between the Hybrid,GA and PSO for minimizing the standard function and it is clear that the Hybrid outperforms GA and PSO.



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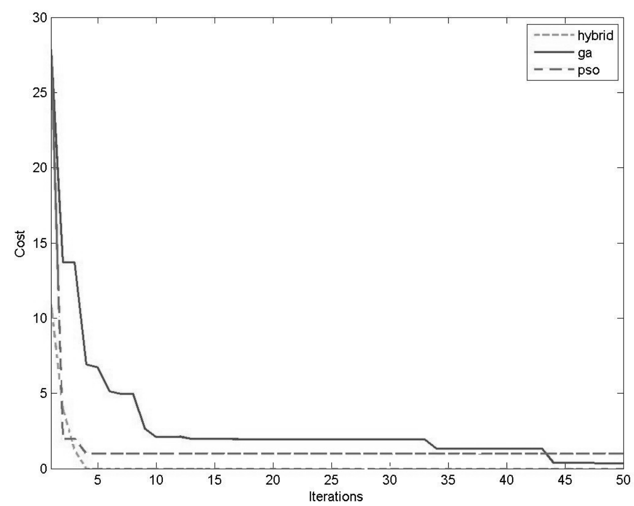

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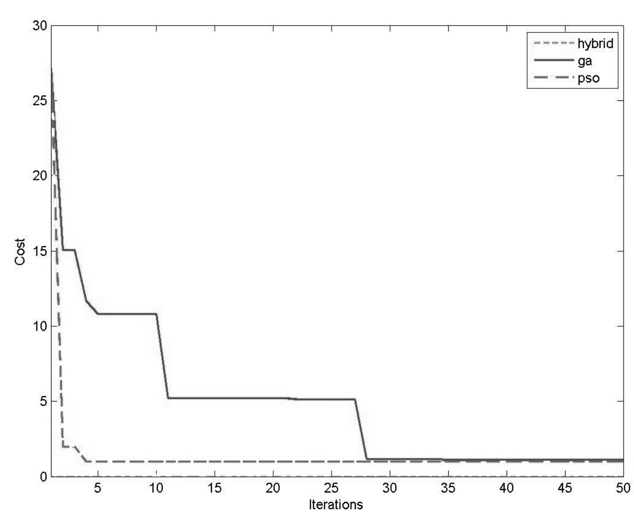


(c) Griewank Function $f(x) = \sum^{d}(\frac{x_i^2}{\ }) - \prod^{d}(cos(\frac{x_i}{\ })) + 1$

Chapter 4

Optimized Histogram Equalization

The proposed Optimized histogram equalization[2] accomplishes the image enhancement i.e,enhancing contrast while preserving brightness of the input image.It performs the job in three distinct phases as :

*phase*1 :Segmention of the original image histogram, based on Otsu's thresholding method.

*phase*2 :Development of weighing constraints for the segmented image[**?**].

*phase*3 : Optimize the weighing constraints using a suitable optimization algorithm[**?**].

4.1 Input image histogram segmentation

Image thresholding is an efficient and quintessential method for the segmenting an input image. A threshold is chosen from the range of pixel values, so as that it can divide the input image into two parts:*the lower gray level of the object* and *the higher gray level of the background*[**?**].Then the object area and the back-ground are flattened out independently so that both the target and foundation can be differentiated successfully.An optimal threshold is the one that efficiently differentiates between the object or the target image and the background.This is achieved by maximizing the inter-class variance. The weighted sum of variances of the two segments,gives inter-class variance which is defined as:

$$\sigma^2(t) = W_L(E(X_L) - E(X))^2 + W_U(E(X_U) - E(X))^2$$

where, $E(X_L)$ = average brightness of the lower gray scale image, $E(X_u)$ = average brightness of the upper gray scale image, $E(X)$ = average brightness of the whole image[**?**]. W_L= cumulative probability of lower class , W_U = cumulative probabilities of upper class, given as

$W_L = \sum_{i=0}^{t} p_i$ and $W_U = \sum_{i=t+1}^{N-1} p_i$

For bi-level thresholding ,the optimal threshold t^* is chosen so as to maximize the inter-class variance $\sigma^2(t)$ follows:

$t^* = max_{0<t<N-1}\sigma^2(t)$

4.2 Development of weighing constraints for the segments

Using the optimal threshold t^* obtained by Otsu's method, the input image histogram ,$F(i,j)$ is segmented into two as $F_L(i,j)$ and $F_U(i,j)$. $P_L(r_k)$ and $P_U(r_k)$ are the Probability Density Functions(PDF) of the respective segments. Then the mean PDF of the segments are found as m_L and m_U.

Transformation limitation for lower sub-image:

The Probability Density Function of the lower sub image is figured utilizing the change capacity $T(.)$ with the accompanying requirements

$P_{LC}(r_k) = T(P_L(r_k)) =$

$$\begin{cases} \alpha & if P_L(r_k) > \alpha \\ \frac{P_L(r_k)-\beta}{\alpha-\beta}^a * \alpha & if \beta \le P_L(r_k) \le \alpha \\ 0 & if P_L(r_k) \le \beta \end{cases}$$

where

$\alpha = b * max(P_L(r_k)), 0.1 \le b \le 1.0,$

$\beta = .0001$ and 'a' represents the power factor , $0.1 \le a \le 1.0$

At that point, the mean PDF ,m_{LC} is ascertained. The mean slip m_{eL} is found as: $m_{eL} = m_{LC} - m_L$.The lapse, m_{eL} is added to $P_{LC}(r_k)$.Finally,the Cumulative Distribution

Capacity (CDF), $C_L(F_L(i,j))$ utilizing the HE methodology is connected utilizing :

$F_L'(i,j) = X_0 + (t^* - X_0)C_L(F_L(i,j))$

Transformation limitation for upper sub-image:

Analogously,the following constraint is applied to the PDFs of upper sub-image.

$$P_{UC}(r_k) = T(P_U(r_k)) = \begin{cases} \delta & if P_U(r_k) > \delta \\ \frac{P_u(r_k)-\phi}{\delta-\phi}^c * \delta & if \phi \le P_U(r_k) \le \delta \\ \phi & if P_U(r_k) \le \phi \end{cases}$$

where

$\delta = d * max(P_U(r_k)), 0.1 \le d \le 1.0,$

$\phi = mean(P_U(r_k))$ and 'c' represents the power factor , $0.1 \le c \le 1.0$

At that point, the mean PDF m_{UC} is computed and the mean lapse m_{eU} is found as: $m_{eU} = m_{UC} - m_U$ and added to $P_{UC}(r_k)$.Finally,the Cumulative Distribution Function (CDF), $C_U(F_U(i,j))$ utilizing HE system is connected utilizing :

$$F_U^{'}(i,j) = (t^* + 1) + (X_N - (t^* + 1))C_U(F_U(i,j))$$

Histogram Equalization Algorithm:

Algorithm 4 Optimized Histogram Equalization Algorithm

Require: An image, $F(i,j)$ with "n" pixels in the gray level range$[X_0, X_{N-1}]$and limitation parameters $a, b, c, d.$

1: Considering the Otsu's threshold,the input image $F(i,j)$ is segmented into lower sub-images $F_L(i,j)$ and upper sub-image $F_U(i,j)$
2: Compute the PDF, $P_L(r_k)$ and $P_U(r_k)$ for the lower and upper sub-images respectively.
3: Apply the constraints a, b to lower sub-image.
4: Apply the constraints c, d to upper sub-image.
5: Independently equalize both the sub-images ($F_L^{'}(i,j)$ and $F_U^{'}(i,j)$).
6: Final image after contrast enhancement is given as:
7: $F_0 = F_L^{'}(i,j) \bigcup F_U^{'}(i,j)$[**?**]

4.3 Optimizing the weighing constraints using Optimization Algorithm

In this proposed Optimized Histogram Equalization algorithm[2],we transormed the probability density function of the lower and upper gray scale image using four parameters namely a, b, c and d . Their optimal values are found using optimization algorithm,in which we have a 4 dimensional population of predefined population size, and two fitness functions i.e; the first one takes care of the contrast by maximizing the difference between DE of original image and contrast enhanced image. The second one,controls the brightness change by minimizing the difference between the mean values of the input and output images.

Discrete entropy: Discrete entropy $E(X)$ is a quality measure for determining amount of information contained in a image.It is defined as

$$E(X) = -\sum_{k=0}^{255} p(X_k) log_2(p(X_k))$$

As DE is the measure of amount of information contained in the image, after image enhancement the information contained in the image must be preserved.Hence the difference in DE value of the original image and the enhanced image should be as low as possible.

Mean Value: Mean is a quality measure for brightness of the image.It is defined as

$$E(X) = \frac{1}{m*n} * \sum_{j=1}^{m} \sum_{i=1}^{n} F(i, j)$$

As mean is the measure of brightness of the image, after image enhancement the brightness should not change abruptly.Hence the difference in mean value of the original image and the enhanced image should be as low as possible.

Algorithm for optimizing parameters:

Algorithm 5 Optimized Histogram Equalization Algorithm

Require: $X(i,j)$ is an image, having 'n' pixels in the gray level range$[X_0, X_{N-1}]$,a, b, c, d.

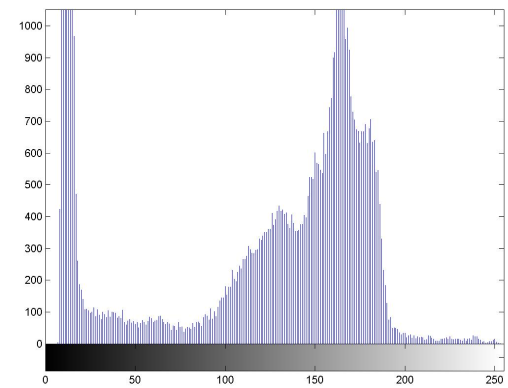
1: Initialize particles a, b, c and d for a predefined population size.
2: Find the values of Fitness functions 1 and 2 which are defined as:
3: Fitness Function 1: Minimize D = DE(original image) - DE(HEed image).
4: Fitness Function 2: Minimize M = Mean(original image) - Mean(HEed image).
5: Fitness Function=D+M[**?**].
6: For each particle a, b, c, generate 'n' random values . That is,
7: a[1],a[2],a[3],...,a[n].
8: b[1],b[2],b[3],...,b[n].
9: c[1],c[2],c[3],...,c[n].
10: d[1],d[2],d[3],...,d[n][**?**].
11: Use optimization algorithm to get the optimal a,b,c,d values using the fitness function F=D+M.

4.4 Histogram equalization Results

In the fig4.3 the original cameraman image along with its Histogram is shown.It also shows the results produced using normal histogram equalization in which contrast is enhanced but brightness is not preserved, whereas in the next figure i.e optimized Histogram Equalization, we see both Contrast Enhanced and brightness preserved.

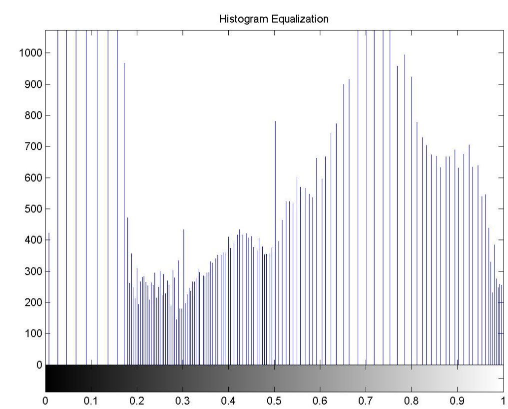
In the fig4.5 we compare the results produced using various optimization algorithms .From the results, we can visualize that the Hybid algorithm produces better image enhancement.

(a) original cameraman image



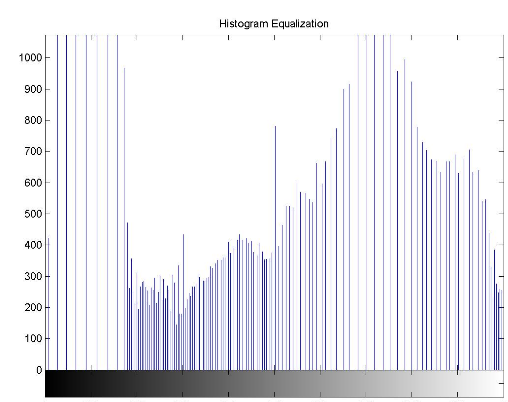
(b) Histogram of cameraman image

(a) Histogram equalized cameraman image(without brightness presevation



(b) Histogram of HE cameraman image

(a) contrast enhanced with brightness preserved



(b) Histogram of enhanced cameraman image

Figure 4.3: Contrast enhancement for cameraman image

4.4.1 Comparision Table

Comparision Table for Cameraman image:

Table 4.1 we see the DE and Mean value of the Hybrid Optimized image is closer to that of the original

Table 4.1: Comparision between GA, PSO, Hybrid optimized HE for Cameraman image

PARAMETERS	ORIGINAL IMAGE	GA OPTIMIZED	PSO OPTIMIZED	HYBRID OPTIMIZED
Discrete Entropy(DE)	7.0097	6.9329	6.9408	6.9613
Mean Value	Mean=118.7245	136.4143	127.8397	121.0151
Number of Generations(NOG)	NA	47	25	21

image. Hence it exhibits better brightness preservation ability while enhancing the contrast .Again we see the number of generations to converge on the optimal values of parameters is least in the case of the Hybrid algorithm.

Similarly we analyse the parameter values of some other standard images.

(a) original cameraman image

(b) GA optimized cameraman image

(c) PSO optimized cameraman image

(d) Hybrid GA-PSO optimized cameraman image

Figure 4.4: Comparision of results of Optimized histogram equalization using GA,PSO, Hybrid GA-PSO

Comparision Table for girl image:

Table 4.2: Comparision between GA, PSO, Hybrid optimized HE for Girl image

PARAMETERS	ORIGINAL IMAGE	GA OPTIMIZED	PSO OPTIMIZED	HYBRID OPTIMIZED
Discrete Entropy(DE)	7.0505	6.8648	6.8823	6.9023
Mean Value	58.8444	59.1212	58.8093	58.6781
Number of Generations(NOG)	NA	60	48	31

Comparision Table for F16 image:

Table 4.3: Comparison between GA, PSO, Hybrid optimized HE for F16 image

PARAMETERS	ORIGINAL IMAGE	GA OPTIMIZED	PSO OPTIMIZED	HYBRID OPTIMIZED
Discrete Entropy(DE)	6.7200	6.7831	6.6956	6.7178
Mean Value	178.6837	100.4041	170.7885	178.5669
Number of Generations(NOG)	NA	95	67	53

Consequently the test image qualities are upgraded utilizing the specified method,measured as a part of terms of measurements such as DE , Mean value and Number of Generations taken to converge to the optimal values.These comparisons quantitatively proves the merits of Optimized Histogram Equalization Methods for being a superior technique for image enhancement.

The above Tables prove that the hybrid optimized method produces better DE and Mean values that are closer to that of the original ones, in less number of generations.This shows that the hybrid optimized histogram equalization accomplishes higher details preservation and optimium contrast enhancement of the input image.

Chapter 5

Conclusion and Future Work

As we know, the histogram equalization technique is successful in improving image contrast, but they normally fail to preserve the input image brightness.The proposed Optimized HE technique has proved to overcome this problem effectively.The proposed method accomplishes a ideal balance between contrast enhancement and brightness preservation. Also we ensured its fidelity using well known parameters like the discrete entropy value which considers the contrast enhancement aspect, the mean value which takes care of the brightness preservation criteria. Unlike the other histogram equalization methods,its computational complexity is very low. After having solved the problem of problems of contrast enhancement and brightness preservation, we had another task of deciding which optimization algorithm to choose for better results. We then used the Genetic algorithm(GA), Particle Swarm optimization(PSO), and a Hybrid GA PSO to optimize the parameters. Based on the results obtained,we saw that the Hybrid Algorithm produced better results in less number of generations,thus proving to have a hand over the conventional GA and PSO algorithm for image Enhancement.

A further step can be to modify the objective functions and perform multi-objective optimization in order to optimize more than one parameter simultaneously to get better image enhancement results.In this case we are focusing only on the DE and the mean values, but other parameters can also contribute for the enhancement process . Also coloured images can be taken into consideration .

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