An Improved Chicken Swarm Optimization Algorithm for Handwritten Document Image Enhancement

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***Abstract*— The Chicken swarm optimization is an upcoming meta-heuristic algorithm which copies the foraging hierarchical behavior of chicken. In this project , we try to learn the preprocessing of handwritten document by contrast enhancement while preserving details using an improved chicken swarm optimization algorithm. The results of the algorithm are compared with other existing meta-heuristic algorithms like Cuckoo Search(CS), Firefly Algorithm(FA) and Artificial Bee Colony(ABC). The proposed algorithm considerably outperforms all the above by giving good results.**

***Keywords*-**Chicken swarm Optimization, Hand written text, Optical Character recognition, meta-heuristic, Image enhancement

I. INTRODUCTION

Effective preprocessing of handwritten text is crucial for Optical Character Recognition (OCR) systems to accurately interpret aged documents or those affected by noise during capture. The degradation of document quality over time, coupled with noise from capturing devices like cameras or scanners, often undermines recognition accuracy. Preprocessing steps aim to mitigate noise and enhance accuracy, with contrast enhancement being a fundamental procedure.

Image enhancement involves improving the visual quality of images to make them look better and more suitable to use for a particular task by reducing noise. In the spatial domain, adjustments are made to the pixel values to achieve the desired enhancement. This adjustment is typically expressed through a mapping function:

$$g(m, n) = T[f(m, n)] \tag{1}$$

Here,

g : represents the enhanced image,

f : denotes the input image, and

T : is the transformation function applied to f to achieve the enhancement.

Given a gray-scale digital Image of size Z = M * N pixels, the number of possible gray levels is L = 256. The histogram of the image h[n] can be expressed as given below:

$$h[n] = \{h_i \in [0, Z] | i = 0,..., L - 1\} \tag{2}$$

where h_i is the frequency of the i^{th} gray level in the image.The most common technique for image contrast improvement is “Histogram Equalization”.

Histogram Equalization (HE) Technique is described as below: Consider an image of M *N pixels. If z_i, for i = 0, 1, 2, ..., L−1 , denotes the gray level range in the image. The probability density function , $p(z_k)$, of intensity level z_k is given by

$$p(z_k) = \frac{n_k}{MN} \quad (3)$$

where n_k is the number of times that intensity z_k occurs in the image and MxN is the image size.

A normalized histogram p[n] of an image which gives the approximate probability density function (PDF) of its pixel intensities is given by:

$$p[n] = h[n]/(M \times N)$$

The Cumulative Distribution Function (CDF) c[n],is obtained from p[n]. HE maps an image into the entire dynamic range i = 0, 1, 2, ..., L − 1 using the cumulative density function mapping T[n] which is given by:

$$T[n] = [(L - 1) * \sum_{(j=0)}^{(n)} (p[j] + 0.5)] \quad (4)$$

where n ∈ [0,(L − 1)] and p[j] is the normalized histogram.

HE gives a flat histogram of an image which may not be exactly uniform because of the discrete nature of the pixel intensities. This results into significant change in the brightness.
The histogram equalization brings large changes to the intensity level values in the image as compared to the original less contrasted image ,thus we need to look into histogram modification techniques which provide us an intermediate histogram which is closer to the original histogram and also to the high contrasted uniform histogram.

This brings us to an optimization problem which can be solved by metaheuristic algorithms like Cuckoo Search(CS),Ant Colony Optimization (ACO),Firefly Algorithm (FF),Genetic Algorithms (GA) ,Chicken Swarm Optimization,etc.A metaheuristic algorithm is a high level procedure designed to find an optimally good solution to an optimization problem with insufficient information or limited computation resource.

In this project we try to learn the Chicken Swarm Optimization algorithm and use its improved version for demonstrating the contrast enhancement for hand-written text image.

Chicken Swarm Optimization (CSO) is a stochastic optimization algorithm proposed by mimicking the hierarchical foraging behavior of chicken in a swarm which gives the optimal solution of a bi-criteria problem of adjusting the contrast level of an image while preserving the details.

II. Literature

1) HISTOGRAM MODIFICATION: As we have observed earlier HE suffers from large backward differences in values of T[n]. So an intermediate image is produced by modifying the input histogram without compromising its contrast enhancement potential. In order to transfer input pixel intensity values to output pixel intensity values, the adjusted histogram can then be added up. The modified histogram can be thought as a solution of a bi-criteria optimization problem where the aim is to find a modified histogram $\hat{h}$ which is closer to a uniformly distributed histogram u but also reduce the residual difference $\hat{h} - h_i$, where h_i is the input histogram. The modified histogram can then be used to obtain the mapping function from eq.(4). This optimization problem can be modeled as a weighted sum of 2 objectives as shown in equation (5) below:

$$min||h - h_i|| + \lambda||h - u|| \quad (5)$$

where $u \in R^{256*1}$ and $\lambda \in [0,\infty)$ is a problem parameter if λ = 0 the Histogram obtained corresponds to the traditional HE and as λ tends to ∞ , it converges to the original image. Thus through varying λ different levels of contrast can be obtained.

2) ADJUSTABLE HISTOGRAM EQUALIZATION:

To solve the optimization problem stated above, we use the sum of squared differences between histograms.

$$\hat{h} = argmin_h ||h - h_i||_2^2 + \lambda||h - u||_2^2 \quad (6)$$

This gives a quadratic optimization problem

$$\hat{h} = argmin_h [(h - h_i)^T (h - h_i) + (h - u)^T (h - u)]$$
(7)

The solution of above equation(7) is

$$\hat{h} = \frac{h_i + \lambda u}{1+\lambda} = (\frac{1}{1+\lambda})h_i + (\frac{\lambda}{1+\lambda})u \quad (8)$$

It can be observed that the $\hat{h}$ is a weighted average of u and h_i. So by adjusting λ, we can easily adjust the level of enhancement.

3) HISTOGRAM SMOOTHING:

While Adjustable Histogram Equalization improves contrast, it also introduces spikes in homogeneous regions of the image. To solve this, we introduce a smoothness constraint to the optimization problem. By adding a term to measure smoothness using the backward difference, we aim to match the original histogram to a smooth distribution instead of a uniform one. The resultant smoothed histogram removes intensity gaps and spikes.[10] The difference matrix $D \in R^{256*256}$ is bi-diagonal with the additional term for smoothness, the optimal trade-off is obtained by

$$min||\hat{h} - h_i||_2^2 + \lambda||h - u||_2^2 + \gamma||Dh||_2^2 \quad (9)$$

whose solution is a three-criterion problem

$$\hat{h} = (1 + \lambda)I + \gamma D^T D)^{-1}(h_i + \lambda u) \quad (10)$$

where λ, the quantity for positioning the amount of contrast on a scale and γ the amount of detail in the image to be retained.

THE CHICKEN SWARM OPTIMIZATION ALGORITHM

The chicken swarm optimization algorithm(CSO) is a metaheuristic algorithm which mimics the hierarchical foraging behavior of chicken [6].

A. Background

Chickens as domestic birds live together in flocks. Their flocking habit is hierarchical in order, with each flock consisting of a dominant rooster, a number of hens and a number of chicks at the lowest level. There exist more dominant hens which are close to the rooster and some submissive ones that stand near the chicks. When a new member is joined, the group gets temporarily disturbed causing disorder. Food access within the group is often dominated by stronger individuals, with the rooster often leading the way and deciding which members get to eat first when food is discovered. This hierarchical behavior is also evident among hens when they are caring for their chicks. This hierarchy plays an important role when it comes to foraging. There is competition for food between different chickens. But the chicks cooperate with each other and search for food around their mother.

B. General Behaviour of Chicken

1) A swarm of chickens is made up of numerous groups, each headed by a rooster and consisting of several hens and chicks.

2) The fitness values determine how the chicken swarm is divided into groups and how each member of the group is assigned a role. The healthiest chickens are selected as roosters, or leaders of a group; the remaining chickens are classified as hens. The chicks are the chickens with the lowest fitness scores. The hens choose their group to reside in at random. Although hens are capable of laying eggs, not all of them will hatch at the same time. Mother-child relationships, or the relationships between chicks and hens in a group, are established at random.

3) After established, the mother-child relationship, dominance relations, and hierarchy order will not alter; updates occur only after every (G) generation.

4) Each group's chickens follow their rooster around in search of food, but they also guard against others stealing their own.Chickens have the ability to haphazardly take delicious food that people have previously discovered. Every chick follows its mother to find food. Food is competitive, and dominant people always have an advantage.

Presumably, the numbers RN, HN, CN, and MN represent the number of hens, roosters, chicks, and mother hens, respectively.

C. Movement of the Chicken

Roosters are the dominant individuals in a group with the best fitness values, and therefore easily find food in a wider space. The position of the rooster is updated as follows:

$$x^{t+1}_{i,j} = x^{t}_{i,j} + Randn(0, \sigma^2) * x^{t}_{i,j} \qquad (11)$$

where $x^{t+1}_{i,j}$, $x^{t}_{i,j}$ are the position of the jth dimension of the chicken i at a time t+1 and t respectively.

Randn(0,σ2) is a Gaussian distribution with mean 0 and standard deviation σ2 defined as shown in eq.(12) below

$$\sigma^2 = \{1 \qquad if \quad f_i \le f_k$$
$$\{ exp\,(\frac{f_k - f_i}{|f_i| + \epsilon}), \; otherwise \qquad (12)$$

where k is the index of the rooster k ∈ [1,N] and k= 1 (randomly selected from a group of roosters),

ϵ, is a number which is small enough to avoid division by 0,

f is the fitness value of the corresponding x.

The position of Hens is updated as follows:

$$x^{t+1}_{i,j} = x^{t}_{i,j} + S1 * Rand(x^{t}_{r1,j} - x^{t}_{i,j}) + S2 * Rand * (x^{t}_{r2,j} - x^{t}_{i,j})$$
(13)

$$S1 = \frac{exp((f_i - f_{r1}))}{abs(f_i) + \epsilon} \qquad (14)$$

$$S2 = exp((f_i - f_i)) \qquad (15)$$

Where Rand is a uniform random number over [0,1] r1 ∈ [1, ...N] is an index of the rooster in the population of hen xi, while r2 ∈ [1,...N] is an index of any other randomly chosen chicken (rooster or hen),from the swarm. r1= r2. All remaining individuals are defined as chick swarms.

The Position of each chick is updated as follows.

$$x^{t+1}_{i,j} = x^{t}_{i,j} + FL * (x^{t}_{m,j} - x^{t}_{i,j}), \quad FL \epsilon\, [0, 2] \qquad (16)$$

where FL is a parameter which indicates that a chick would follow its mother in foraging for food, $x^{t}_{m,j}$ is the position index of the i^{th} chick's mother.

D. Improving Chicken Swarm Optimization

Results from experiments conducted reveal that the original CSO can easily fall into local optimum and converges prematurely for high dimensional problems[6]. To end this, an improved chicken swarm optimization was proposed by making the following observations and changes. According to eq (17),Chicks can only learn from their mothers but not the roosters.Thus, the chicks will easily fall into local optimum along with their mothers.To avoid this, the Chicks have to learn from both their mothers and the roosters in a group.Therefore the position information of the chicks is updated according to the positions of their own mother and rooster in the group using eq. (17) which is a modification for eq.(16) [8].

$$x_{i,j}^{t+1} = s * x_{i,j}^{t} + FL * (x_{m,j}^{t} - x_{i,j}^{t}) + F * (x_{r,j}^{t} - x_{i,j}^{t}) \quad (17)$$

where s is the self-learning coefficient for the chicks ,
m is the position of the ith chick's mother,
r is the position of the rooster.
F is a learning factor, indicating that the chicks would also follow the rooster in search of food. [8].

E. The Improved Chicken Swarm Optimization Algorithm

The improved algorithm is as follows

1) Take an Initial value of N (population of chickens) and also define the other parameter values like RH,HN,CN, MN,update frequency of the chicken swarm G,maximum number of generations, etc.

2) Take the initial value of the lower bound lu and upper bound up using the gray levels of the image.

3) Take a population $x = (x_1,x_2,...x_N)$ of N chickens from random solutions.

4) Evaluate the fitness(x_i) and find the best solution x_{best} of the chicken swarm.

5) for t=1:itermax

6)f (t%G == 0) Determine the link between the chicks and their mother hens in a group by sorting the fitness values of the chickens and dividing the swarm into multiple subpopulations (Roosters, Hens, and Chicks).

7) end if

8) Update each chicken in the swarm based on its category; for roosters, use eq. (11) and assess their fitness; for hens, use eq. (13) and assess their fitness; and for chicks, use eq. (17) and assess their fitness.

9) Both the global ideal position x_{best} and the personal best position x* i should be updated.

10) end for

11) output the optimum value x_{best}

Ⅲ . CONTRIBUTION

Image Contrast Enhancement can thus be understood as an image histogram optimization problem where we try to find a histogram that reduces the "cost function" provided by equation (9) ,whose solution given by equation (10) (a is a three-criterion problem).So for finding an optimal value of the modified histogram for our image for contrast enhancement we will use the Improved Chicken Swarm Optimization Algorithm with the equation (9) being the fitness function.

A. Algorithm used is:-

1) Input an gray-scale image and extract the matrix of the input image.

2) Calculate and draw the histogram, h[n], for the image matrix obtained.

3) Take appropriate values for parameters, λ (amount of contrast), and γ, (the amount of detail to be retained).

4)To smooth the histogram, find a difference matrix, D, that has the histogram's backward difference.

5)Now apply the Improved Chicken Swarm Optimization algorithm to get the optimized histogram,with parameters : Maximal generations (iterations)Itermax, Population size N, Dimension D, G, The number of roosters in the RN,The quantity of hens in HN,The number of Chicks CN residents,The size of the mother hen population MN, the difference matrix D, the input histogram h[n], and λ and γ.To smooth the histogram, find a difference matrix, D, that has the histogram's backward difference.

6)Find out the normalized histogram, p[n] from the optimized histogram using the expression below:

p[n] = h[n]/Number Of Pixels

7) From p[n], one can get the approximate Cumulative Distribution Function (PDF), or c[n].S

8) Use the modified histogram in th equation (4) to map the image to a final contrasted image in spatial domain.This gives us our required enhanced image.

9) After this the performance metrics are calculated for analyzing the performance of our algorithm.

B. Parameter variation and Analysis:-

After performing the experimentation the following facts were identified:

1) It is better to keep a greater number of hens than roosters thus RN < HN. All hens lay eggs, but all the eggs do not hatch at the same time, thus in a swarm HN >MN, Each mother hen can give birth to more than one chick, but it has been assumed that the number of adult chickens is more than that of the chicks. Thus implying CN < MN .

2) The number of times the hierarchical structure of the chicken changes(G) impacts the convergence rate of the ICSO algorithm. If it is large ,the algorithm takes a higher amount of time to converge to a global best solution and end its execution but if it was too small, the quality of the image was not good.

3) The self-learning coefficient for the chicks s decreases exponentially from 0.9 to 0.4 with increase in the number of iterations. s varies according to eq.(18)

$$s = s_{min} * \left(\frac{s_{max}}{s_{min}}\right)^{(1/(1+10*t/Itermax))} \quad (18)$$

where s_{min} is the final value of the iterations, s_{max} is the initial value of the iterations, t is the current value of the iterations, Itermax is the maximum number of iterations.

4) The Value of λ, (the amount of contrast) is usually kept between 0-20 and γ (the amount of detail in the image to be retained) is varied between $1000 - 10^9$.

5) The obtained results were compared with other algorithms keeping all the general parameters of these algorithms, such as population size, dimensions and maximum number of generations, the same for an unbiased comparison. of.

C. Quality measures:-

We try to compare the performance of various metaheuristic optimization algorithms using : entropy of the images, mean, variance and the PSNR (Peak Signal to NoiseRatio). The expressions for the same are presented below:-

1) The mean squared error (MSE) is defined as the average of the squares of the ”errors” between the original image and our enhanced image.The MSE of images F(i, j) with respect to input image I (i, j) is given by:

$$MSE = \frac{\sum_{j=1}^{N}\left(\sum_{i=1}^{M}(F(i,j)-I(i,j))^2\right)}{MN} \quad (19)$$

Peak signal to noise ratio is given as follows :

$$PSNR = 20log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \quad (20)$$

2) According to Shannon the entropy ,the Entropy of the image is calculated using the formula below

$$H(X) = \sum_{i=1}^{n} P(x_i)I(x_i) =- \sum_{i=1}^{n} log_b P(x_i) \quad (21)$$

where b is the base of the logarithm.

3) If zi, i = 0, 1, 2, ..., L − 1 , represent the values of pixel intensities in an M ∗ N image. The probability, $p(z_k)$, of intensity level z_k in a digital image is

$$p(z_k) = \frac{n_k}{MN} \quad (22)$$

where n_k is the frequency of the intensity z_k in the image and MN is the image size. Thus the Mean intensity m of the image is given by

$$m = \sum_{k=0}^{L-1} z_k p(z_k) = 1 \quad (23)$$

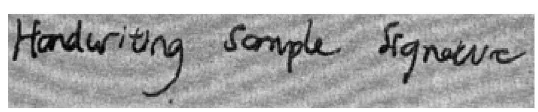
And the variance of intensities,which is the measure of how intensity values are scattered about mean intensity , is given by

$$\sigma^2 = \sum_{k=0}^{L-1}(z_k - m)^2 p(z_k) \quad (24)$$

IV Results and Conclusion

We have implemented only the Improved Chicken Swarm algorithm .For understanding the differences between the results of this algorithm and the results of other meta-heuristic optimization algorithms we present the data provided by the research paper :

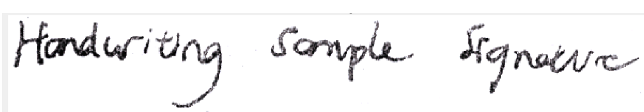
Obtained for the below image for given parameters:



Algorithm	Parameters	Values
ICSO	Population of chickens N	20
	RN	0.05*N
	HN	0.75*N
	MN	0.1 * HN

	CN	N-RN-CN
	G	10
	F	0.4
	FL	rand[0.4,1]
Cuckoo Search	Population of Cuckoos	20
	Discovery Rate	0.25
	α	1
Firefly	Population of fire flies	20
	α	0.5
	β_{min}	0.2
	γ	1
ABC	Population of Bees	20

The output image for ICSO and the corresponding PSNR , Var, Mean and entropy are given below . The results from other algorithms is also presented (just for comparison not implemented) :-



Entropy	Original Image	6.8835
	FF	2.0588
	CS	1.2734
	ABC	1.1145
	ICSO	**0.9824**
PSNR	FF	24.4208
	CS	24.1181
	ABC	24.179
	ICSO	**24.0908**
Mean	FF	231.4378
	CS	238.3807
	ABC	238.8735
	ICSO	**243.3040**
Var	FF	63.2248
	CS	53.8975
	ABC	54.4533
	ICSO	**44.0278**

We can see from the obtained numerical values that it is better to use the ICSO algorithm over other optimization algorithms.

So we can conclude there are many algorithms for image enhancement but the key challenge is maintaining uniform luminance in an image while preserving the details. These two constraints contradict each other thus we need to get a balance between them . Hence we need to have a method to increase contrast while preserving detail. So in this project we implemented the enhancement of handwritten document images using an improved Chicken swarm optimization algorithm. We optimized the input histogram with the improved Chicken swarm algorithm while increasing the contrast and preserving details to improve recognition accuracy.

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