Turkish Online Journal of Qualitative Inquiry (TOJQI)
Volume 12, Issue 6, June 2021: 1238-1252

Multi-objective Cuckoo Search in Image Visi-bility Improvement

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Abstract

Atmospheric Phenomenons like haze, fog, mist, dart are produced due to tiny suspended particles floating in the air which scatter, reflect, refract, absorb light in all directions spherically. As a result , natural images captured under the influence of such turbid weather are prone to produce degraded visibility leading to fatal accidents in computer vi-sion applications.Single image visibility techniques are the most challenging of all models in visibility improvement and solely obey the restoration based optical image formation model. Existing single image dehazing estimates atmospheric light (AL) and transmission by some prior information manu-ally. In this paper, we experimented the robustness of the Lévy distribution of Cuckoo Search Algorithm(CSA) in tuning a new multi-objective image performance function PPS for adaptable dehazing which estimates and achieves balance between correlation ,noise, and geometrical information of image . Two parameters, AL and Depth Map (DM), are optimised with levy steps in the search space of CSA to produce the best dehaze image . GT O-Haze, DerainNet, Frida synthetic dataset have been used for evaluations and the presented method is compared with the state-of-the art techniques qualitatively and quantitatively for dehazing obtaining satisfactory results .

Keywords: Image recovery model, Quality Assessment, CSA, Dehazing, extinction coefficient, fitness function, PCC, Lévy flight

1. Introduction

Image with fine details is the key for image analysis, extraction. Haze, fog, suspended particles in the atmosphere cause obstacles in visibility in images due to the scattering of light in the media by those suspended particles [1, 2]. Visibility is one of the research sought after topics during the last decade. Thousands of research papers found to address

the problem [3]. Several techniques have been proposed till date. As the problem is ill posed NP-Hard and prediction based, no single method can validate the problem. Dehazing, defogging, deraining techniques are classified into three wide classes, i. Image enhancement based, ii. Image Fusion based and iii. Image Restoration based [3]. Image Enhancement method takes care of contrast and visual effect of image without taking care of image degradation. Image fusion-based method highlights the maximization of information from multiple sources of images. Image restoration-based method finds the optical based physics model to invert the degraded image transmission and compensate the distortion by some statistical prior to get a clear image. Among the three categories, image restoration methods can address the dehaze problem precisely until now. The image formation optical model was first proposed 10] and improved[11]. In [9] proposed image formation scattering model to fix the problem of poor visibility in digital images solving the inverse model with scattered and attenuated relative pixel flux estimation. The estimated attenuated map was subtracted from the hazy image to produce a clear image. and a temporal filter was introduced to solve the problem [9]. The work of [9] has been improved contrast ,and wavelength in [4]. Single gray image to colour image were experimented with two prior conditions, i. the contrast of a clear image is higher compared to a hazed image, ii. field spots (pixels of interest) attenuate as a continuous function of distance, and eventually flat/ regular at a distance. The novel estimated prior above describes that there is no correlation between object surface shading and the transmission map. Independent component analysis (ICA) and a Markov random field (MRF) model was adopted to estimate the surface radiance. Thus, it quantified transmission of the scene and restored the visibility of the degraded image [5]. An integrated system of browsing, enhancing, and manipulating outdoor images integrated with GIS-based digital terrain and urban models were presented. Thus, the generated image is of high quality, clear, but requires expensive infrastructure and used offline processing [29]. Dark channel prior (DCP) is undoubtedly a milestone work of dehazing problems. It triumphs over the drawbacks of the above-mentioned algorithms. Clear image has minimum intensity in a patch out of a colour channel. This principle is the soul of the model, which is then applied to the atmospheric scattering model and developed marvelous results. It combines with soft matting for master stroking the restoring image, which is responsible for high computational complexity [6]. Fast contrast-based enhancements to remove haze with linear complexity were developed. The atmospheric veil function was considered locally changeable slowly, thus extinction coefficient of medium was estimated. Transmission coefficients of the atmosphere were obscured with pretreatment and median filtering. Heterogeneous medium was pretreated with white balance for smoothing [7]. It is a non-local prior with nonuniform degradation. Proposed method introduced that colours of haze free image are clustered firmly and rolled over the entire RGB image depending on their different transmission coefficients. Whereas a hazy image forms strong colour lines those were clustered previously- the haze line. This haze line regenerates distance map and haze free image. The algorithm is linear, faster, deterministic, no training is required [8]. In [30] 2017 a novel idea was introduced with the DnCNN model that utilized batch normalization and residual connection for blind Gaussian denoising. Basically, DnCNN is a Trainable Non-linear Reaction Diffusion (TNRD) Model for fast and effective image restoration [30]. In [31] described TNRD (Trainable Nonlinear Reaction Diffusion) based image restoration with a highly parameterized linear filter followed by highly parameterized influence functions through training of a loss-based approach. It is equally applicable for image Gaussian denoising, super resolution, and deblocking [31]. Contrast of hazy images were enhanced by minimum information loss as cost function compensation. Static images and video are processed in real time. Flickering artifacts in video and ringing artifacts in still images are removed [35]. Inhomogeneous illumination is corrected with B-spline shading model optimisation parameter and compared to Shannon's entropy on Parzen windowing. Gradient-based optimization algorithms efficiently use the derivatives of entropy. This work investigates extensively on large retinal images to improve inhomogeneity in illumination [36]. PSAC (Photoshop Auto Contrast algorithm) is widely used in photoshop images for contrast improvement [37]. Tang studied thoroughly different haze-relevant features, specially DCP with a learning framework for optimum dehazing feature classification. The synthetic hazy dataset, as a training set, found effective for dehazing real world data [38]. Real time single image retinex based color preservation method for defogging is presented. The method restores clear image from foggy image with real colour and real time basis [39]. DCNN model-based rain streaks were removed from images. Model was trained with DerainNet. Derained image improved the resulting image and compared with benchmark methods [42]. It is a non-parametric unsupervised multi-level adaptive discriminative grey level thresholding model. It is stable and classifies image globally [53].

2.Contribution:

Atmospheric image formation model is totally based on estimation of noise and pixel intensity of a degraded image [3,4,5,6,7,12,13,14,15].Most of the estimations are handcrafted. Automated or adaptable estimation can only be achieved by metaheuristic optimizations [55,56,57,58,59,60, 61]. Considering above all, we are proposing two estimations, i) Adaptable Atmospheric Light, ii) Adaptable Depth Estimation with multimodal object function due to the highly nonlinear nature of the problem in the fitness landscape. In subsequent sections, it will be shown how these two parameters play pivotal roles in reconstruction of original scene radiance. Two estimation methods will be shown separately as well as in conjunction with their performance measures both qualitatively and quantitatively.

Figure 1. L-R: Degraded Image, Clear Image

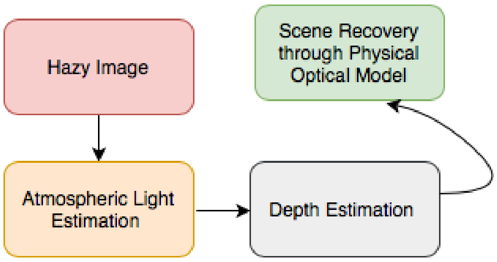

Figure 2. Image Formation Scattering Model

3.Proposed Approach with Related work

Restoration based Single RGB image dehazing in figure 2 is a research hotspot recently and depends on some prior [4-9]. Bio-inspired metaheuristic optimisation is a promising area of image restoration [46,58,60,62]. Dehazed image quality is optimised by newly formulated fitness function PCS through AL and DM tuning via Levy Flight. [58,60].

3.1. Physical based optical scattering model

This model is based on Mie scattering [10,11]. This model was first experimented to improve image quality under poor visibility conditions [9]. This problem has become a Research promising area since then.Camera captures images . Image is captured by camera or sensor. It is the union of two parts, i) direct light attenuated from the scene to the camera, and ii) light scattered through atmosphere light ending up at the camera. Thus, the final image at the observation point is blurry, low contrast, poor visibility and noisy. This mechanism is expressed in figure 1 and figure 2 and represented by equation (1)

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \qquad (1)$$

where I(x) is a degraded image, J(x) represents original scene radiance, t(x) is transmission map, and A as atmospheric light. J(x) has to be developed from I(x), t(x), and A whereas t(x) and A are unknown. Efficient estimation of t(x) and A is the key to effective haze removal. t(x) is estimated from depth estimation from a single image. J(x)t(x) term is known as direct attenuation as original scene radiance reduces exponentially with distance. A(1-t(x)) is called atmospheric veil/airlight/atmospheric scattering light which causes shifts of colour, and degradation of scene. Transmission is represented by equation (2). d represents distance and β is the extinction coefficient of medium of propagation.

$$t = e^{-\beta d} \qquad (2)$$

$$I_{cmin} = \left(\min_{c \in \{r,g,b\}} I^c(x)\right) \qquad (3)$$

Ic and Icmin indicate individual channels of an image (RGB/ multispectral) and minimum of three or multi-channels respectively. I_{cmin} produces a depth map in the simplest way [14,15,32]. I_{cmin} is henceforth assumed as a raw depth map and guides to recover haze free images by reducing noise. In this work, minimum noise depth map is achieved by smoothing via Lévy steps adaptively.

$$I_{cminLevy} = Levy(I_{cmin}) \quad (4)$$

Equation (4) represents clean minimum intensity 2D map noise free as low as possible as in Algorithm II. Lévy step is used as the window size of the order statistic filter that has been used on equation (3). Levy step-based window of min-OSF refines depth estimation while preserving edge information. OS represents non-linear, invar-iant discrete filters for time series analysis. Strength of this filter is easy to implement and suppress impulse noise while preserving edge details in image [62, 63].

Thus, this can be useful and treated as a depth map. Further, this channel gets normalised for use in transmission estimation. Compliment of this equation will produce maximum intensity channels to reconstruct prominent im-age structure and reduced computational complexity and are easy to implement for transmission estimation t(x). With Levy steps, good quality haze-free images will be generated without compromising the important structure of the original image. Depth map generation with minimum patch estimation is more accurate, but computationally expensive [7]. Final refined transmission is represented by equation (5).

$$t_{new}(x) = 1 - kI_{cminLevy} \quad (5)$$

t_{new}, k represents refined transmission and a correction parameter for aerial perspective respectively [33,34]. The concept of k (0-1) is defined as, haziness factor for visibility correction [7,12,13,14,15,32] and has chosen dynamic for flexible, visually pleasing images. Atmospheric light is estimated as the average of the top 1%-pixel intensity of each channel. Atmospheric light is revived through levy flight as shown in equation (6). Random val-ue of Lévy steps is applied as a tuning factor for setting atmospheric light. Original scene radiance J(x) is restored as in Eq. (7). This method is shown in Algorithm I.

$$A_{new}(x) = Levy(A) \quad (6)$$

$$J(x) = \frac{I(x)-A}{max\ (t(x),t_0)} + A \quad (7)$$

The model of equation (7) retrieves back original scene radiance provided ideal atmospheric light A and ideal transmission t have been achieved. But this is extremely difficult to obtain. Only approximation through prior estimation can be provided. In this context, estimation through metaheuristic optimisation based algorithms perform well. In this paper, CSA (cuckoo search algorithm) has been used for the estimation of atmospheric light and transmission of scene radiance.

3.2.Bio-Inspired Algorithm

Researchers are always inspired by rich resources of nature. Most of the new algorithms are nature following due to the inclination towards green environment and adaptation and adherence to environment. This has been found that these types of algorithms are grafted and fitted well with the object of interest. They basically follow the mechanism of biology, physics, and or chemistry. Due to the inspiration from nature, these algorithms are often referred to as Bio-Inspired/ Nature-Inspired Algorithms.

Now, real-world optimization problems face different challenges for solving and sometimes unable to solve at all like NP-Hard problems. In such situations, optimisation tools are preferred, but no promise of optimal solution. As a result, trial and error with optimisation techniques are being used to solve the problems. In such cases, this has been found that those nature-inspired algorithms prove efficient results and gain popularity. In current research work, more than 40 different variants of nature-inspired algorithms are there with increasing trends of thousands of research papers [54].

3.3.Importance of Cuckoo Search Inspired Algorithm

In connection with the above, Cuckoo Search (CS) (2009), a variant of nature-inspired algorithm, has attained much attention due to its fast-problem-solving capability effectively. Brood parasitism of Cuckoo species has been incorporated sophisticatedly for numerical optimisation and continuous problem initially. Instantly, re-searchers jumped and tested with benchmark functions to compare with PSO, GA, and found remarkable better results. Since then researchers are looking after these algorithms for applications and improvements. Multimodal optimization problems can be solved with CS efficiently. Since 2009, a variety of CS has emerged. Few of the trends are shown in figure 3. Cuckoo Search along with its variants are applicable in every field of engineering, industry, medical, drug manufacturing.

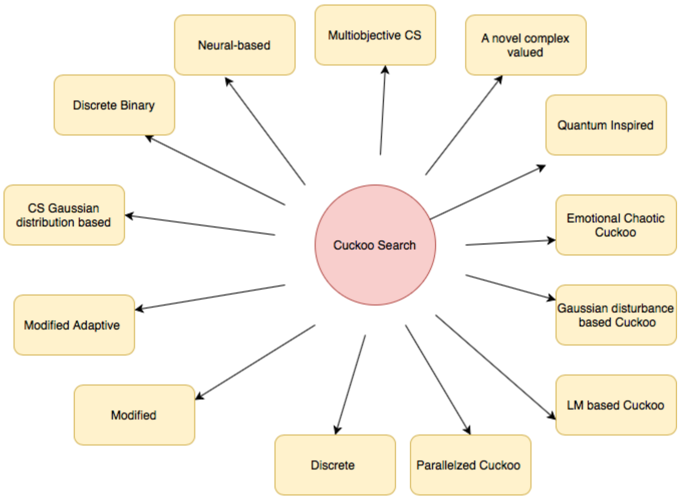

Figure 3 Cuckoo Search Variants

3.4.Randomization and Levy Flight

After an optimisation problem formulated, the most challenging task is to find out the optimal solution. As al-ready discussed, in the case of NP-Hard, optimal solutions in most of the cases are extremely difficult or may be unrealisable. Search space plays an important role in optimisation solution results. Random walk is the concept that gives the feasibility to find the efficient search space for convergence of optimal solutions. Here comes the concept of metaheuristic stochastic optimisation. Metaheuristic develops randomisation of local search with global scale. Heuristic algorithms are trial and error basis exhaustive search. Whereas, metaheuristic is faster and converges quickly with random search space. Random variables are defined by probability distributions. Phone calls are defined by Poisson probability distributions.

$$p(n;\lambda) = \frac{\lambda^n e^{-\lambda}}{n!}, (n = 0,1,2, \dots \dots \dots) \qquad (8)$$

□□ >0, where □□ is the mean or expectation of occurrence in a given interval. Many more distributions are Gaussian, Impulse, Rayleigh, Nakagami, etc. In this connection, metaheuristics often follow Lévy distribution and this distribution is very popular and amazing. N is independent distributed random identical variables. Fourier transform of its sum is given by

$$F_N(k) = exp(-n|K|\beta) \qquad (9)$$

The equation (9) describes the Lévy distribution. But it's time domain representation is not straightforward or as expected. Rather, it is represented by

$$L(s) = \frac{1}{\pi}\int_0^{\propto} cos(\tau s)\, e^{-\alpha\tau^{\beta}} d\tau, (0 < \beta \leq 2) \qquad (10)$$

L(s) represents Lévy distribution with index □□ in the range zero to two. The parameter □□ is set as one.

Case I: □□=1, integral becomes Cauchy distribution,

Case II: □□ =2, integral represents normal distribution. L(s) follows Brownian motion.

Integral of Equation (10) represents asymptotic series and its leading-order approximation of the flight length ensures power-law distribution

$$L(s) \sim |s|^{-1-\beta} \qquad (11)$$

Thus equation (11) represents heavy-tailed distribution with infinite variance for 0<□□<2. The moments diverge to infinity for 0<□□<2 leading to a stumbling block mathematical analysis.[54]. Objective Function Formulation and why?Single Objective Function vs. Multiple Objective Function:Most of our real world problems are multi-objectives rather than single objective[54]. Strength of the proposed algorithm: Good global convergence, tradeoff between global and local optimality with random walk via Lévy flight.CS performs better than other contempo-rary algorithms in many applications.CSA (2009) is still research hot spot due its simplicity, few parameters set-tings, ease of hybridization compared to GA, PSO etc. [56].

Foundation of dehazing techniques is rooted on strong priors like DCP, NLP [9,17]. Due to its inherent NP-Hard computational complexity, these prior-based techniques are difficult in applications. Metaheuristic Optimizations are well-known for efficient results in image reconstruction [18,44]. Designing fitness functions by selecting suitable tuning parameters of metaheuristic algorithms are popular. GA (Genetic Algorithm), PSO (Particle Swarm Optimization), Swarm Intelligence (SI), Cuckoo Search (CS) are leading bio-inspired algorithms [1, 2,5]. CS proves robust and efficient in converging quickly with its two tuning parameters [3,4,5,6,16] and it has Levy Flight and Intrusion reproductive strategy known as brood parasitism [5]. Two parameters are probability of discovering eggs P_a [0 1]and number of nests n [5, 10, 15,….]. x (t+1) stands for new solution where i is symbolised as cuckoo, then a Levy Flight is denoted by

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \leq Le'vy(\lambda) \qquad (12)$$

Now, equation (12) represents the stochastic random walk developed from Markov chain and $\alpha > 0$ from equation (8) is the adjustable Lévy step size following the scale of the problem of interest. $\oplus$ stands for exclusive OR as entry wise multiplication. The random walk via Lévy Flight is stable system with step size increasing exponentially as it converges following Lévy distribution given by equation (11), Random walk via Lévy flight is far efficient than PSO due to its step size which fluctuates efficiently to find local minima globally. This plan prevents the object function trapping in local minima.

3.5.Parameter setting

These parameters are as p [0. 0.01. 0.05, 0.1,0.15, 0.2, 0.25,0.3, 0.4, 0.5], and n[5, 10, 15, 20,25,30,40,50,100, 150,250, 500] [45, 46]. □□=1; (1<□□ ≦3).

pa defines the probability of finding a nest.

n signifies the number of nests.

CS Algorithms Description

Algorithm I_0

CSA via Lévy Flight

begin

Objective function

Find cuckoo randomly by Lévy Flights

Evaluate its quality/fitness and nest

worse nests are abandoned and new ones are built;

Keep the best solutions

End

3.6.Fitness Function (Object Function) Design

Fitness Function (FF) is the figure of merit of a system that is close to a solution to its desired goal. It is achieved by optimising FF. FF may be single objective or multi-objective [48]. With the increase of image-based applica-tions, reliable and effective images are the requirements, consequently automated image parametric evaluation becomes essential to fit faster applications. Quantitative and quantitative parameters become the sole responsi-ble metric for image evaluation. Followings are few of them which are used frequently for image restoration ap-plications in quantitative evaluations. These metrics can be used as FFs. Now, individual metrics will be consid-ered as single FF. Whereas, by combining these metrics, multimodal fitness function is proposed to get complex information for better performance instead of monomode fitness function. All the parameters used are very rele-vant for structural information of an image with the amount noise present. PCC, SSIM metric refer to the struc-tural information, and PSNR identifies noise presents in the image retrieved. All the three metrics are positive high value for good mapping between two images.For efficient performance of these coefficients (Pearson Correlation Coefficient, PSNR, SSIM) high values are expected.

Pierson correlation coefficient

Sir Francis Galton (1885) defined theoretical development of regression and correlation in statistical topics.

Karl Pearson (1895) subsequently following the work published the Pearson's Correlation Coefficient (PCC). PCC is treated extensively in statistical analysis, pattern recognition, and image processing. In image processing, two images of the same type and size are compared with PCC. PCC measures the dissimilarity between the two images-es. Its mathematical representation is shown below [57]. Algorithms.

$$PCC = \frac{\sum_i (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_i (x_i - x_m)^2}\sqrt{\sum_i (x_i - y_m)^2}} \qquad (13)$$

x_i, y_i represents its pixel intensity of image1 and image 2 respectively. Whereas, x_m , y_m represents its mean pixel intensity of image1 and image 2 respectively

PSNR (Peak Signal-to-Noise ratio) is a well-known parameter in image evaluation and stands by the ratio the maximum possible power of a signal to the power of corrupting noise that affects the fidelity. The peak error between the reconstructed image and original image is quantified in terms of PSNR. The higher value of PSNR is expected and indicates low noise, higher quality image. MSE (Mean Square Error) is first computed. MSE refers to the cumulative difference between the two images as said. Small value of MSE is appreciated and improves image quality and reduces the error. This is represented by:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \qquad (14)$$

I(i,j) is an image of size (m, n) noise-free monochrome image and K(i,j) is its noisy version. MSE is mean square error.

$$PSNR = 20log_{10}\left(\frac{MAX_I^2}{MSE}\right) \qquad (15)$$

MAX_I is the maximum possible intensity value of image

SSIM (Structural Similarity Index): It is a metric to measure the similarity between two images. Range ([0 1]. High value is desirable [49]. It is Human Visual System (HVS) based metric

$$\boldsymbol{SSIM(x,y) = \frac{(2\mu_x\mu_{y+}c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}}$$

(16)

μ_x, μ_y indicates the average of x and y respectively. σ_x, σ_y symbolize the variance of x, y respectively. σ_{xy} is the covariance of x and y. c1=(k1L), c2=(k2L) are two variables for stabilizing the weak denominator, k1=0.01, k2=0.03 taken. L represents the dynamic range of the pixel value, 2n -1. n is the number of bits, n=8 normally.

3.7. Multiobjective Fitness Function

Most of the engineering problems in the real world are multi objective, complex, nonlinear constraints. Hence, the nature of the problem of multi objectives are very different from that of single objectives. Metaheuristics approach performs significantly better in such scenarios [59]

Adaptable atmospheric light and why: Most of the dehazing techniques adopt uniform atmospheric light as A. This works well so far. It is about 0.1% of the brightest pixels of the Dark channel [6]. In reality, this is nonuniform and dynamic in nature. Thus, we propose adaptable atmospheric light with the steps of Lévy flight to converge multimodal fitness function in the defined search space.

Adaptable Depth Map and why? Estimation of depth of scene will lead to production transmission of scene recovery as well as suppression of noise and attenuation.

Adaptable Atmospheric Light and Depth Map through Lévy steps and why? Combining the above-mentioned techniques, original scene radiance can be approximated as close as original.

In Spite of all disparity, efficient multiobjective metaheuristic algorithms have many successful applications [59]. CSA has been proven very exciting and efficient in engineering design applications and outperforms existing Metaheuristic algorithms like PSO.

PCC, PSNR, SSIM are image quality metrics. Each of them are equally important to verify the effectiveness for image improvement. In this work, we propose a novel multi-objective fitness function **PPS** which combines the effectiveness of the above mentioned three quality metrics catering noise minimization, correlation maximisation, and maximising geometric similarity. Resulting best dehazed image is produced by optimizing PPS with CSA. Two tuning parameters are AI and DM window parameter alpha via Lévy step in search space.

This is defined as follows:

$$PPC = PCC * PSNR * SSIM \quad (17)$$

The effectiveness of equation (17) is observed in three different algorithms. Part I: Adaptive Atmospheric Estimation with Lévy Steps, Part II: Adaptive Depth MapEstimation with Lévy Steps, and finally Part III: Adaptable Atmospheric Light and Depth Estimated Visibility Improvement. These steps have been shown as follow in Table I along with block diagram in figure 4:

Table I: Algorithms of the proposed model

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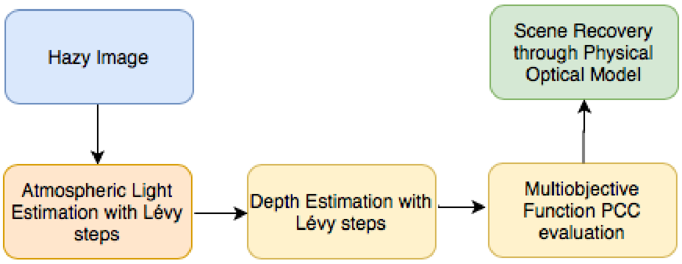
Adaptive Atmospheric Estimation with Levy Steps : Part-I Algorithm I	Adaptive Depth MapEstimation with Levy Steps:Part-II Algorithm II	Adaptable Atmospheric Light and Depth Estimated Visibility Improvement:Part-III Algorithm III
Start	Start	Start
Step I: Get Input Image	Step I: Get Input Image	Step I: Get Input Image
Step II: Objective Function PCS Formulation	Step II: Objective Function PCS Formulation	Step II: Objective Function PCS Formulation
Step III:Optimized Atmospheric Light via tuning Levy steps	Step III: Optimized Atmospheric Light via tuning Levy steps	StepIII: Optimized Atmospheric Light via tuning Levy steps
StepIV:Optimized quantisation level of Otsu's multi-thresholding via Levy steps	Step IV: Optimized quantisation level of Otsu's multi-thresholding via Levy steps	Step IV: Optimized quantisation level of Otsu's multi-thresholding via Levy steps
Step V: DM Refinement from step IV	Step V: DM Refinement from step IV	Step V: DM Refinement from step IV
Step IV: Maximising fitness function PCS	Step IV: Maximising fitness function PCS	Step IV: Maximising fitness function PCS
Step IV: Best Dehazed output with Inverting Image Formation Scattering model	Step IV: Best Dehazed output with Inverting Image Formation Scattering model	Step IV: Best Dehazed output with Inverting Image Formation Scattering model
End	End	End

Figure 4. Block diagram of the proposed model



4.Experiments

Our model is experimented on synthetic and natural hazy image datasets [Frida, He, O-Haze] and compared with ten state-of-the art methods objectively and subjectively. We provide qualitative results to illustrate our superior performance on generating perceptually pleasing and haze-free images. The experiment is run on Matlab 2018a. Figure 5 shows from left to right original hazy image, its depth, transmission and rectified with image formation scattering model.

Figure 5. L-R: Low visibility, Depth map, Transmission Map, Improved Visibility

4.1.Subjective Evaluation of Various Methods on

O-Haze, Frida, He and rain dataset are selected for our comparison experiment [6,42,43] and are performed with our algorithm and compared and eight benchmark algorithms. The results of ours are really satisfactory shown in table I, I, III, and IV and figure 6a,6b. six images are extracted from [6,42,43, frida]. These six images are treated with Algorithm I, II, III. Their results are clear, color balanced, halo free. Parametric report is shown in table II, III, IV, where PCC, PSNR, SSIM, and PPS are evaluated and compared. Reports show satisfactory results. In figure 7, 8, and 9 Quality analysis shows better results than other techniques.

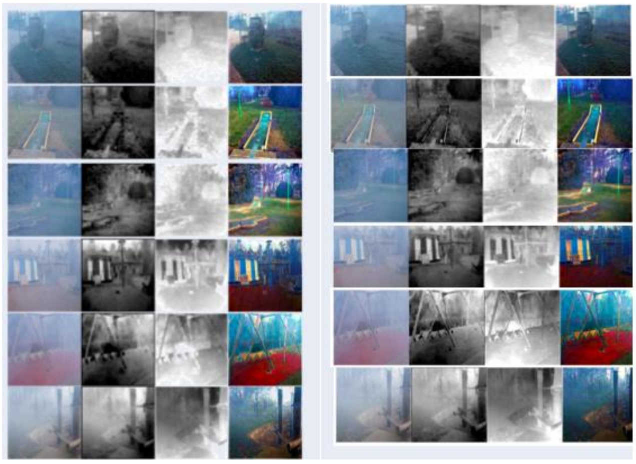


Figure 6a. Six images with Algorithm I(left), and Algorithm II(right)

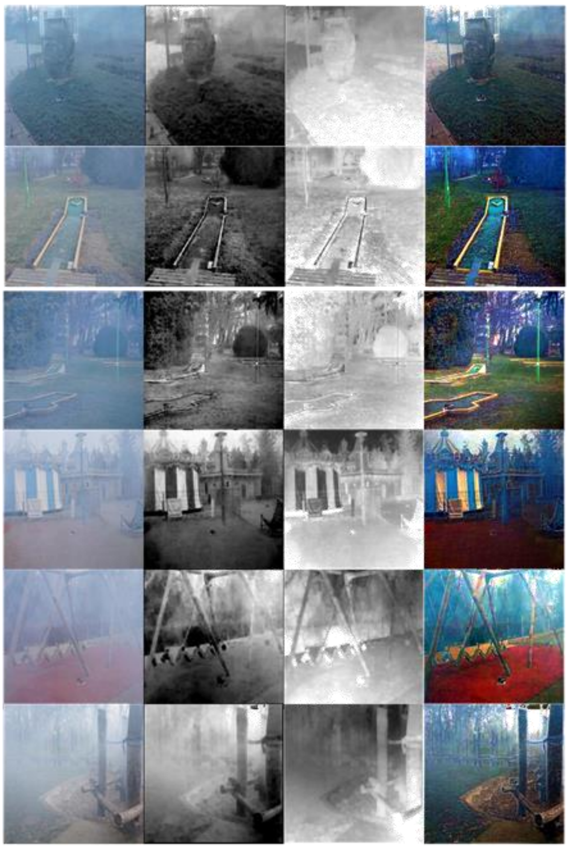


Figure 6b. Six images with Algorithm III

4.2.Quantitative Assessment

Subjective tests are human oriented, biased, and expensive [41]; quantitative assessments are effective, inexpensive. PSNR, SSIM, Entropy, compression ratio are few criteria for effective image quality assessment. In Table II, III, and IV, performance of six images are evaluated with three objective parameters-PCC, SSIM, PSNR. Their objective results are in figure 6. Experimental results show that the proposed model is efficient and effective .

Table II: Image Performance with PPS (Object Function/ Fitness Function) with Algorithm I Depth Map alpha (window size): 5x5; Pa= 0.25; Number of nest N=25(Figure 6a)						
Lévy step	Iteration	Atmospheric light(R,G,B)	PCC	PSNR	SSIM	PPS (normalized)
1.3479	50	0.9667 , 0.9757 , 0.9787	0.18122	54.1259	0.9803	9.61589
2.8713	10	0.8046, 0.8404, 0.9323	0.1743	51.344713	0.9579	8.5731
1.3136	25	0.9736 , 0.9723 , 0.9797	0.1206	51.8577	0.9691	6.0634
1.1749	25	0.9948, 0.9996 , 0.9974	0.1805	49.7684	0.9199	8.2635
1.575	34	0.9759 , 0.9864 , 0.9897	0.1712	51.3355	0.9514	8.3623
1.8704	21	0.9516 , 0.9657 0.9746	0.1716	51.1475	0.9457	8.3002

Table III: Image Performance with PPS (Object Function/ Fitness Function) with Algorithm II Atmospheric Light: A(R)= 0.9941 A(G)=0.9972 A(B)=0.9979; Pa= 0.25; Number of nest N=25,						
Lévy step	Iteration	Depth Map (Alpha)	PCC	PSNR	SSIM	PPS (normalized)
1.5633	46	2	0.1837	53.5901	0.9774	9.6238
1.7349	75	5	0.1791	50.4169	0.9413	8.5013
1.6521	25	2	0.1221	51.6085	0.9648	6.0809
2.3579	25	4	0.1802	49.6938	0.9182	8.2222
1.6617	26	4	0.1719	51.0037	0.9464	8.2994
1.18	59	3	0.1742	50.2288	0.9298	8.1371

Table IV: Image Performance with PPS (Object Function/ Fitness Function) with Algorithm III Pa= 0.25; Number of nest N=25, (Figure 6b)							
Lévy step	Iteration	Atmospheric Light(R,G,B)	Depth Map (Alpha)	PCC	PSNR	SSIM	PPS (normalized)
1.2513	50	0.9738 0.9813 0.9833	2	0.1825	53.8065	0.9785	9.6091
2.3465	23	0.8421 0.8692 0.9482	4	0.1752	50.9257	0.9511	8.4843
1.313	125	0.9711 0.9693 0.9777	2	0.1212	51.6932	0.9662	6.0531
2.1469	25	0.9840 0.9923 0.9912	4	0.1794	49.7516	0.9194	8.2073
2.09	78	0.9498 0.9697 0.9787	4	0.1686	51.4941	0.9534	8.2764
2.4765	92	0.9526 0.9664 0.9751	4	0.171	51.0242	0.944	8.235

4.3.Comparative Analysis:

In figure 7 and table II, subjective and objective analysis of one sample image [42] have been performed with eight methods and ours. As reflected from table II, our approach outperforms in PSNR, SSIM, and CNR. Therefore, the testing report finds good results.

Figure 7. L-R :1sr Row-Hazy, He, Kim13, Kolar, Meng13; 2nd row- PSAC, Tang14, Tarel09, Xiao12, Ours

Table V: Quantitative analysis with Figure 7										
Dataset	**Parameter**	**He[6]**	**Kim[35]**	**Kolar[36]**	**Meng[3]**	**PSAC[37]**	**Tang[38]**	**Tarel[7]**	**Xiao[39]**	**Ours**
IVZ	PSNR/ SSIM	8.3683/ 0.4742	11.3911/ 0.6242	16.8533/ 0.7613	8.3556/ 0.3220	14.0170/ 0.7642	8.2530/ 0.3408	19.4574/ 0.8022	14.9015/ 0.6589	10.3267/ 0.4310
	BRISQE/ NIQE	13.9234/ 3.9057	27.5536/ 4.0779	16.1231/ 3.4152	14.8344/ 3.9095	15.833/ 3.3367	12.2248/ 4.0374	23.9818/ 3.6162	28.3196/ 3.7914	22.1891/ 6.0818

Figure 8. L-R: Hazy, He, Fattal, Kopf, Tan, Tarel, Ours with PCC, SSIM, PSNR

Figure 9. Top Row, L-R: GT, Hazy, Hist EQ, Adapt. Histeq, Imadjust, He, Meng; Bottom Row. L-R: Meng, Fattal, Berman, DehazeNet, Ren, Ancuti, Ours

Our algorithms outperform other algorithms in comparative evaluation (subjective and objective) in figure 7,8,9. Moreover, Visibility increases appreciably without halo effect

Settings for the Simulations

MatLab2018a

CSA algorithm for Matlab version [44] with Pa=0.25, n=15

Image scattering model for Dehazing method [13,14,15,32]

Workstation setup: Apple MacBook Air

5.Discussion, Shortcoming, And Future Scope

This paper describes Cuckoo Search Optimization-based single RGB image dehazing. Atmospheric light and depth estimation refined with Lévy steps of CSA which in turn optimizes multi-objective fitness function PPS. PPS is the enhancing quantity metrics of image reconstruction i.e., Pearson Correlation Coefficient, PSNR, SSIM. This proposed method utilizes efficient step fluctuations to converge local optima globally by random walk strategy. Substantial simulations with comparative analysis have been reported with O-Haze dataset outdoor images. Results are acceptable and support the robustness of our algorithm with dense haze images. In all the images, the proposed methods perform best results both quality and quantity-wise. Random walk makes the proposed algorithm automated to find the optimum airlight and depth estimation. Thus, very high-quality scene radiance is able to produce in each case. Manually, this may be very tedious or may be impossible. Multiobjective function is very difficult to solve. Here, we have resolved the problem successfully and a new multi objective function PPS has been designed successfully for dehazing problems.

Author’s Contribution: All authors are having equal contributions.

Ethics: This work is a new idea. It has not been published anywhere.

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