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LEVY DISTRIBUTED DIRECTIONAL SHRINKING SEARCH OPTIMIZATION (DSSO) BASED IMAGE ENHANCEMENT ON NANO LC IMAGES

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ABSTRACT

Enhancement of images plays a very vital role in digital image processing. Its major objective is to identify important visual features based upon applications from a given image. Automatic Image enhancement is formulated as nonlinear optimization problem with several constraints and since then from last one-decade optimization algorithms have been extensively used to solve them. In this paper, an improved Directional shrinking search optimization (DSSO) algorithm has been used to enhance images of Nano Liquid Crystals. This improved method has the ability to explore and exploit the problem domain region efficiently. In DSSO the search region shrinks gradually and providing ample scope to exploit the region using less computation time. To exhibit the enhancement capability of our proposed algorithm, it has been compared with a classical nature inspired Particle swarm optimization (PSO) algorithm. The parameters like peak signal to noise ratio (PSNR), entropy, standard deviation (SD) and numbers of edges in an image has been calculated for comparison. Both qualitative and quantitative analysis has been done on the enhanced images, which clearly demonstrates the capability feature of improvised DSSO over PSO.

KEYWORDS

Digital Image Processing; Directional Shrinking Search Optimization (DSSO), Particle Swarm Optimization (PSO), Peak Signal to Noise Ratio (PSNR), Entropy, Standard Deviation (SD).

1. INTRODUCTION

Liquid crystals (LCs) are having both mobility order, self- assembled and soft materials at molecular, supra-molecular and macroscopic levels (Goodby JW et al., 2008, Tschierske C., 2007, Kato T et al., 2006). For the past and present decade, LCs are having a variety of applications based on display technology in holography, biosensors and electro-optic filters (Vardanyan K. K. et al., 2011, Eskalen H. et al., 2015). These are very important because of the materials showing different physical properties like optical, electrical, magnetic, mechanical etc. (Dummur D.A. et al., 1978, Auernhammer G.K et al., 2009, Mottram N. J. et al., 2006) and also optically anisotropic. In the research point of view nano particles are doped in to LC gives an emergent application in nanoscience, digital image processing and nanotechnology (Haraguchi F. et al., 2007, Miyama T. et al., 2004, Shiraishi Y. et al., 2002, Tripathi et al. 2020).

With increasing impact of technology in our lives, visual information plays a very vital role. To extract visual information from digital images, the procedure adopted is image enhancement. It is a special procedure using which images are processed and then vital information's are extracted out. Image enhancement technique facilitates the human visual system to visualize an image and its features clearly, so that the image can be used for further intended applications.

Image enhancement techniques are generally based upon spatial domain

(Huang S-C et al. 2013, Celik T and Li H-C., 2016) or in frequency domain (Tang J et al. 2003, Mukherjee J and Mitra SK., 2008). The computational complexity and the need of more parameters makes frequency domain techniques more complicated compared to spatial domain enhancement techniques.

The design of an enhancement technique depends primarily upon the intended application. The category of most common contrast enhancement techniques comes Global Histogram Equalization (GHE) (Cheng H and Shi X., 2004). In this the narrow histogram of the original image is stretched upon the overall gray region to increase the contrast of the image. Here due to excessive stretch the images generally lose their natural appearance. To overcome this shortfall many more approaches were proposed like Brightness Preserving Bi-Histogram Equalization (BBHE) (Kim, Y. 1997), Dualistic Sub Image Histogram Equalization (DSIHE) (Wan Y. et al. 1999), Dynamic Histogram Equalization (DHE) (Ibrahim H. and Kong N. S. P., 2007) and Brightness Preserving Dynamic Histogram Equalization (Hojat et al. 2008) etc. The computational complexities of these techniques are very high and also lag in stretching the histogram uniformly over the dynamic range. Hence fails to provide satisfactory contrast enhancement of the image.

From last decade, Image contrast enhancement techniques have been designed as an optimization problem and different optimization algorithms exclusively used to solve these problems effectively. Some of

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these soft computing techniques like Genetic algorithm (GA), Particle swarm optimization (PSO) used to enhance the contrast of the image (Gorai A. and Ghosh A., 2009, Zhang, C.-J. and Hu, M., 2008, Hashemi et al 2010). From complexity and computational time point of view PSO works better than GA as it does not required operations such as selection, crossover and mutation to converge to global optimum solution.

In this paper an improved levy based Directional Shrinking Search Optimization (DSSO) has been used to enhance the contrast of images of compounds prepared using Butyl Benzoic acid (4ba) added with various concentrations of ZnO (Zinc Oxide) at different transition temperatures. Experimental calculation has been done by calculating PSNR, Standard Deviation, Entropy and number of edges present in the image and comparison has been done with PSO based enhancement technique with same objective function.

2. EXPERIMENTAL PROCEDURE TO DEVELOP LC COMPOUND

For our research LC compound butyl benzoic acid (4ba) has been purchased from Sigma-Aldrich laboratories (St. Louis, MO, USA). Using Autoclave method, the ZnO nano particle suspension are synthesized. The LC compounds are prepared using standard procedure (Jayaprada P. et al. 2016).

3. DESIGN OF TRANSFER FUNCTION AND OBJECTIVE FUNCTION

In spatial domain method of image enhancement, a transfer function has to be designed to map every pixel from original image to the enhanced image. If $F(m,n)$ indicates the gray intensity value of the (m,n) th position pixel in the original image, $G(m,n)$ indicates the gray intensity value of the (m,n) th position pixel in the enhanced image and taking into account both local and global parameters under consideration, then the transfer function (Malik Braik et al. 2007) used to obtain enhanced image is given by

$$G(m,n) = K(m,n) * [F(m,n) - q * M(m,n)] + M(m,n)^p \quad (1)$$

Where q and p are the parameters associated with local mean $M(m,n)$ of the (m,n) th pixel over a $i \times i$ window. While $K(m,n)$ indicates a function related to Mean and standard deviation of the original image.

The required mean $M(m,n)$ can be calculated using the expression given below

$$M(m,n) = \frac{1}{i \times i} \sum_{x=0}^{i-1} \sum_{y=0}^{i-1} f(x,y) \quad (2)$$

Whereas the function $K(m,n)$ is given by

$$k(m,n) = \frac{r * D}{\sigma(m,n) + s} \quad (3)$$

Here r and s are the parameters. D denotes to global mean of the original input image and $\sigma(m,n)$ is the local standard deviation computed using a window of size $i \times i$. The overall transformation takes place around the global mean of the image and variation in contrast takes place due to these constraints parameters having ranges are $p \in [0, 1.5]$, $q \in [0, D/2]$, $r \in [0, 1]$ and $s \in [0.5, 1.5]$.

While performing the enhancement using optimization algorithm, the design of the fitness or objective function plays a very vital role. The quality of the enhanced image depends upon the value of objective function. In literature many objective functions has been presented (Jingquan S. et al. 2003, Runqiu G et al. 2004). The objective function for the optimization is given below

$$F_{enhance} = \log(\log(E(I_{enhance}))) * \frac{N_{edges}(I_{enhance})}{m * n} * H(I_{enhance}) \quad (4)$$

Where $F_{enhance}$ indicates the fitness value, $E(I_{enhance})$ indicates the sum of intensities of the edge pixels value, N_{edges} indicates the number of edge pixels detected using sobel edge operator. $H(I_{enhance})$ indicates the enhanced image entropy and finally, M and N indicates the total number of pixels along row and column. All the above parameters depends upon

the parameters p, q, r and s . The optimization algorithm maximizes $F_{enhance}$, so that the optimize values of p, q, r and s can be utilized for image enhancement.

4. PROPOSED ALGORITHM

Any optimization algorithm performance depends upon two factors i.e. Exploration and Exploitation. How efficiently in a minimum computational time any algorithm explores and exploit the search region to obtain the global convergence point indicates its robustness. In most of the practical application-based optimization problems the search region expands exponentially with increase in the dimensions of its variables. So generally, it leads to decrease in convergence rate and increase in probability to be trap in local optimum solution. This problem is common in most of the classical optimization algorithm.

DSSO (Directional Shrinking Search Optimization) (Tripathi D P and Jena U R, 2017) algorithm is a fast optimization algorithm capable to escape from being caught in local optimum solution in any optimization problem search space.

In this proposed improved Levy distributed DSSO algorithm, all the randomly generated points (particles) in the search space are made to shift directly in a proportionate amount towards the optimum solution at any instant of time. At every instant of iteration, all the points are directed towards optimum point controlled by corresponding magic parameter value. This magic parameter values are generated from the unit vector between each points and the optimum value point at that instant. This magic parameter is a position dependent stochastic inertia weight associated with every particle with different value based upon its distance from the instant best point. This variable inertia weight concept helps each particle to explore the search region exhaustively. So, to enhance the high exploration capability of the algorithm this stochastic magic factor has been added during iterations.

To reduce the computational time to converge and to avoid unnecessary wandering of points in search space, a control over the search region has been made by calculating the minimum and maximum dimensional value of the points in each successive interval. These values will create optimum search space or a local boundary for the algorithm to do searching the optimum best solution. This process will iteratively shrink the search region for the algorithm at every instant.

This property of directional movements of points and shrinking of search region enables a better a exploration and exploitation capability to the algorithm to find a global minima point in a defined search region. Moreover, to enhance the feature of better exploitation of the shrink region a stochastic levy distribution has been done to enable the particles to efficiently search in the shrink region.

The Levy distributed DSSO algorithm is described as below:

1. Randomly initialize the current population points in the search space. The k th point in the search space is given by

$$X_k = (X_{k1}, X_{k2}, X_{k3}, \dots, X_{kd}) \quad (5)$$

Where k varies from 1 to N (number of points) and $d \in [1, D(\text{dimension})]$.

2. Evaluate the objective function $f(x_k)$ for every point in the search space.
3. Find out the minimum fitness and its corresponding position in search space as G_{min} and G_{best} respectively. Begin the iteration till the stopping criteria does not satisfy.
4. Evaluate the Euclidean distance between the G_{best} and all the other points in the search space.

$$r_{dist,k} = \|G_{best} - X_k\| \quad \text{where } k \text{ varies from } 1 \text{ to } N \quad (6)$$

5. The directional property of every point towards minima best point is obtained by calculating unit vector

$$\text{position_vector}_k = (G_{best} - X_k) \quad \text{where } k \text{ varies from } 1 \text{ to } N$$

$$\text{unit_directional_vector}_k = \frac{\text{position_vector}_k}{r_{dist,k}} \quad (7)$$

6. Evaluate Magic factor $fact_k$:

$$fact_k = \sum_{j=1}^{dim} unit_directional_vector_{k,j} \times \rho \quad (8)$$

where ρ varies from 0.5 to 1.5.

7. Now update the position of points in the search space using expression given below

$$x_{k,j} = fact_k \times x_{k,j} + rand(0,1) \times (G_{best,j} - x_{k,j}) \quad (9)$$

Where k varies from 1 to N and j varies from 1 to dimension

8. Updated shrinking region

$$\text{Updated Max.dimension} = \max(x_k) + \alpha \quad (10)$$

$$\text{Updated Min.dimension} = \min(x_k) + \alpha \quad (11)$$

Where α is kept at 0.2 to give some variance to the shrink region. This updated dimension will provide the probable search region.

9. Evaluate the objective function again for all points in the search space and update value of G_{min} and G_{best} values using greedy technique.
10. Putting boundary constraints to the population using the boundary condition obtained from step 8.
11. For better exploitation of the probable search region, points are stochastically made vary in the search region using Golden expression based on Levy Flight (Chechkin et al. 2008), where number of steps taken is N , dimension is dim and the power law index is kept 1.8.
12. The stochastically generated points are given by the expression $x_k = x_k * \text{Golden expression}$, where k varies from 1 to N
13. End the iterations; if termination criteria do not satisfy, begin the loop from step 3.

5. RESULT ANALYSIS

In this proposed work, we have formulated the image enhancement technique as an optimization problem. The algorithm is implemented using MATLAB2013a. The LC images (Fig. 1- Fig. 9) used over here belong to compounds prepared using Butyl Benzoic Acid (4ba) with dispersed ZnO nps with various concentration at different transition temperatures. The major aim of this work is to visualize each texture details clearly and retaining the original color texture of the images.

The qualitative analysis indicates the clarity in human visual perception of an enhanced image. The original LC images are compared with output enhanced images obtained from enhancement technique using PSO and LDSSO. The output images obtained from enhancement technique using LDSSO is superior in terms of preservation of enhancement of contrast and brightness. Moreover the original color is preserved in the proposed technique as shown if Fig.1-Fig.9.

To support the result of qualitative analysis, the quantitative analysis parameter chosen over here are entropy, Standard deviation (SD), PSNR and number of Edges in the images. The experimental values for the stated parameters are shown in Table(1-4). Higher value of entropy indicates the informative richness of an image. Entropy of an enhanced image using LDSSO is 2.1% more than the PSO based technique. Peak Signal to Noise ratio of an enhanced image is always less than the original image. Empirical calculation clearly indicates PSNR of output images based on LDSSO is 31.8% more than the PSO based technique. Standard deviation of an image indicates how well the pixels intensities are spread across the dynamic range 0-255. Higher is the value of SD, more clarity is observed in enhanced image. The value of SD is 9.2% more in LDSSO based technique than PSO based enhancement technique.

Edges of the objects in an image are directly related to the contrast of an image. Higher is the value of this parameter means image is very well perceived by human eye. In LDSSO based enhanced images the number of edges are about 2.77% more than the original images whereas in PSO based enhancement technique the number of edges are 1.40% more than the original images. The calculated values for qualitative parameters indicate that improved LDSSO based enhancement technique is better compared to PSO based enhancement technique.

Table 1: Entropy for the Butyl Benzoic acid(4ba) compounds images obtained using PSO and LDSSO based Image Enhancement Techniques

Sl.No	Images	Enhancement Technique using	
		PSO	LDSSO
1	4BA Pure Nematic at 111.0 °C	1. 7.1360	2. 7.2255
2	4BA Pure Nematic at 102.9 °C	3. 7.0191	4. 7.2065
3	4BA Pure Nematic-Solid at 94.3 °C	6.9656	7.1335
4	4BA+1% ZnO Nematic droplets at 107.6 °C	6.7741	6.9315
5	4BA+1% ZnO Nematic at 85.9 °C	7.4283	7.5768
6	4BA+1.5% ZnO Nematic droplets at 105.8 °C	7.0817	7.2276
7	4BA+1.5% ZnO Nematic at 102.3 °C	7.4025	7.8524
8	4BA+1.5% ZnO Nematic-Solid at 85.9 °C	7.3935	7.4651
9	4BA+1.5% ZnO Solid at 68.3 °C	7.0847	7.1832

Table 2: PSNR for the Butyl Benzoic acid(4ba) compounds images obtained using PSO and LDSSO based Image Enhancement Techniques

Sl.No.	Images	Enhancement Technique using	
		PSO	LDSSO
1	4BA Pure Nematic at 111.0 °C	18.3881	12.4904
2	4BA Pure Nematic at 102.9 °C	18.4285	17.2118
3	4BA Pure Nematic-Solid at 94.3 °C	22.6817	19.7579
4	4BA+1% ZnO Nematic droplets at 107.6 °C	23.9261	17.8567
5	4BA+1% ZnO Nematic at 85.9 °C	21.8227	15.7144
6	4BA+1.5% ZnO Nematic droplets at 105.8 °C	23.1502	17.0738
7	4BA+1.5% ZnO Nematic at 102.3 °C	22.0621	16.2548
8	4BA+1.5% ZnO Nematic-Solid at 85.9 °C	21.0516	15.1187
9	4BA+1.5% ZnO Solid at 68.3 °C	20.4786	14.5124

Table 3: Standard deviation (SD) for the Butyl Benzoic acid (4ba) compounds images obtained using PSO and LDSSO based Image Enhancement Techniques

Sl.No	Images	Enhancement Technique using	
		PSO	LDSSO
1	4BA Pure Nematic at 111.0 °C	39.794	41.4115
2	4BA Pure Nematic at 102.9 °C	43.722	46.6638
3	4BA Pure Nematic-Solid at 94.3 °C	42.255	47.6523
4	4BA+1% ZnO Nematic droplets at 107.6 °C	35.0361	38.3829
5	4BA+1% ZnO Nematic at 85.9 °C	47.855	53.6867
6	4BA+1.5% ZnO Nematic droplets at 105.8 °C	39.5481	43.2155
7	4BA+1.5% ZnO Nematic at 102.3 °C	44.2407	48.5404
8	4BA+1.5% ZnO Nematic-Solid at 85.9 °C	50.8752	55.3977
9	4BA+1.5% ZnO Solid at 68.3 °C	47.4529	52.5129

Table 4: Total Number of Edges for the Butyl Benzoic acid (4ba) compounds images obtained using PSO and LDSSO based Image Enhancement Techniques

Sl.No.	Images	Original	Enhancement Technique using	
			PSO	LDSSO
1	4BA Pure Nematic at 111.0 °C	3013	3182	3228
2	4BA Pure Nematic at 102.9 °C	2411	2482	2565
3	4BA Pure Nematic-Solid at 94.3 °C	2103	2114	2125
4	4BA+1% ZnO Nematic droplets at 107.6 °C	3316	3424	3563
5	4BA+1% ZnO Nematic at 85.9 °C	2773	2781	2786
6	4BA+1.5% ZnO Nematic droplets at 105.8 °C	2896	3000	3045
7	4BA+1.5% ZnO Nematic at 102.3 °C	2404	2422	2452
8	4BA+1.5% ZnO Nematic-Solid at 85.9 °C	2842	2861	2928
9	4BA+1.5% ZnO Solid at 68.3 °C	2901	2914	2923

Figure 1: LC original and optimized enhanced images of 4BA Pure Nematic at 111.0 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 2:** LC original and optimized enhanced images of 4BA Pure Nematic at 102.9 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 3:** LC original and optimized enhanced images of 4BA Pure Nematic-Solid at 94.3 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 4:** LC original and optimized enhanced images of 4BA+1% ZnO Nematic droplets at 107.6 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 5:** LC original and optimized enhanced images of 4BA+1% ZnO Nematic at 85.9 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 6:** LC original and optimized enhanced images of 4BA+1.5% ZnO Nematic droplets at 105.8 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 7:** LC original and optimized enhanced images of 4BA+1.5% ZnO Nematic at 102.3 °C (a) Original image, (b) using PSO , (c) using LDSSO **Figure 8:** LC original and optimized enhanced images of 4BA+1.5% ZnO Nematic-Solid at 85.9 °C (a) Original image, (b) using PSO (c) using LDSSO **Figure 9:** LC original and optimized enhanced images of 4BA+1.5% ZnO Solid at 68.3 °C (a) Original image, (b) using PSO (c) using LDSSO

6. CONCLUSION

In this proposed work the images of LC compounds dispersed with various concentrations of ZnO nps at different transition temperatures are captured using POM (Polarizing Optical Microscope) and their optical texture have been enhanced using the proposed LDSSO. Comparison based on qualitative and quantitative analysis clearly indicates the robustness of the proposed enhancement algorithm.

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