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Implementation of Modified Particle Swarm Optimization Algorithm for Image Contrast Enhancement

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Abstract*: - *Image contrast enhancement is mostly preferred approach for Medical Image Processing field. In this work, a new Histogram Specification (HS) based image contrast enhancement scheme is described. The optimal values of the weighing constraints are progressed through the standard of Modified Particle Swarm Optimization (MPSO) with respect to the histogram of the input processed images. The proposed scheme improves the contrast of the input processed image superior than its existing histogram equalization methods. Henceforth, this method can efficiently be utilized in the fields including image processing, electronics etc. The overall evaluation of the HS scheme can be computed by means of Discrete Entropy (DE) and Contrast Improvement Index (CII).

Keywords*: *Contrast Improvement Index, Contrast enhancement, Discrete Entropy, Histogram Equalization, Histogram Specification, Image enhancement, Particle Swarm Optimization.

I. INTRODUCTION

In Medical Image Processing field, the image contrast enhancement is typically preferred model for improving the Input Processed Image (IPI). It objectives is to subjective visual enhancement of a specified IPI by varying the intensities of its pixels [15]. Usually, image enhancement purposes to enlarge the intensity differences between the foreground objects and background of an IPI.

Histogram Equalization (HE) is a modest as well as efficient system for improving the contrast of an IPI [1]. HE, consuming a discrete cumulative histogram of the IPI, creates uniform distribution over the dynamic intensity principles of the IPI pixels to generate a better image. The foremost issue of HE is that the mean shift invariably outcomes in an extreme aberration in the mean brightness of IPI.

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Brightness Preserving Bi-Histogram Equalization (BBHE) will be a modified HE model which classified the IPI into two sub-images depends on its mean and the equalization is implemented individually for the partitioned images [2]. BBHE reserves the unique intensity of an IPI. Though, it generates unsolicited pieces in the improved IPI. Dualistic Sub-Image Histogram Equalization (DSIHE) can be a modest deviation of BBHE that carefully splits the image histogram depends on the cumulative probability density with respect to the threshold grey level of 0.5 [3]. Recursive Mean Separate HE (RMSHE) [4] is a new scheme that recursively divides the histogram of an IPI based on its mean. In this scheme, though some regions of the histogram cannot be prolonged knowingly, the outliers that enlarge build unsolicited pieces. This will be a collective shortcoming of the majority of the current histogram segregating schemes meanwhile they fix the dividing conditions as invariant during the procedure of equalization.

Recursive Sub-Image Histogram Equalization (RSIHE) [6] is alternative recursive scheme similar to RMSHE in which the histogram is recursively segregated; depend on the median instead of mean. This scheme yields 2i pieces of sub-histograms (where 'i' is the recursion depth). But, it is very problematic to identify the optimal rate of 'i'.

Weighted Thresholded Histogram Equalization (WTHE) [7], Image Inversion and Bi-Level HE (IIBLHE) [8], and image edge and contrast enhancement scheme by means of Unsharp Masking and constrained HE [9] are all devised in such a way as to alter the histogram of the IPI by weighing and thresholding earlier to HE, and all have the benefit of scalability. Recursively Separated and Weighted Histogram Equalization (RSWHE) is another scheme in which the IPI histogram is partitioned into two or more sub-histograms periodically [10]. A considering progression is then passed on these sub-histograms autonomously and HE procedure is passed lastly on the weighted sub-histograms. But, the recursive formulation of the weighing component for every sub-histogram undesirably enhances the computational complexity of this scheme.

Histogram Specification (HS) is alternative scheme in which the predictable output image histogram is organized by stipulating the preferred output histogram. HS converts the histogram of IPI with respect to the stated histogram to highlight particular gray level ranges. This transformation can simply be talented by stating the output histogram explicitly.

Nevertheless, stating the output histogram pattern is not an easy mission as it differs with IPI [1].

In this work, a new image contrast enhancement scheme, called Optimized Histogram Specification (OHS) is established, which alters the histogram of an IPI through optimal constraints earlier to the application of HS. The optimal rates of the limits are estimated by means of Modified Particle Swarm Optimization (MPSO).

The principle of basic histogram equalization is deliberated in section 2 and section 3 provides the principle of histogram specification. In section 4, OHS algorithm is specified. The results are stated in section 5 and conclusion in section 6.

II. BASIC HISTOGRAM EQUALIZATION

A digital image is designated by Z={Z(i, j)}, where Z(i, j) indicates the gray level of a pixel at (i, j). Let M be the total number of pixels in the IPI and intensity of IPI is divided into K levels as $\{Z_0, Z_1, ..., Z_{K-1}\}$. Hence, it is clear that $Z(i, j) \in \{Z_0, Z_1, ..., Z_{K-1}\} \ \forall \ (i, j)$. Let t_k signifies the total number of pixels with gray level Z_q in the IPI. The PDF (Probability Density Function) of Z_q is specified as:

$$p(Z_q) = \frac{tq}{M}, q = 0, 1, ..., K-1 \quad (1)$$

The histogram of an IPI is stated as plot between $p(Z_q)$ and Z_q. The cumulative density function (CDF) with respect to PDF is stated as follows:

$$S_q = c(Z_q) = \sum_{i=0}^{q} p(Z_i) \quad (2)$$

while q = 0, 1 ,..., K-1 and it is recognized as $c(Z_{K-1})=1$. Moreover, the transformation function of HE is stated as follows:

$$f(Z_q) = Z_0 + (Z_{K-1} - Z_0) \times c(Z_q), q = 0, 1, ..., K-1 \quad (3)$$

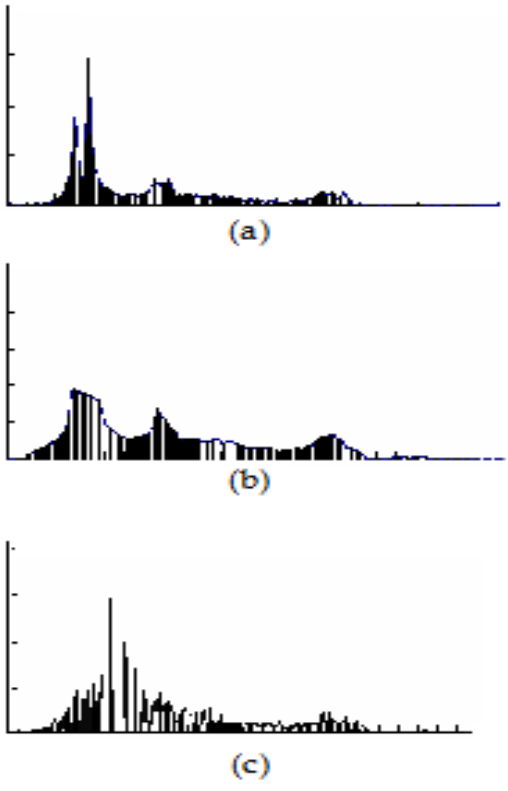


Fig. 1. (a) Initial Histogram (b) Specified Histogram (c) Equalized Histogram using HS

III. HISTOGRAM SPECIFICATION

Histogram specification is employed while the histogram of an image is to be converted into a stated histogram to accomplish highlighted gray level ranges. Besides, the CDF of the stated histogram is stated as:

$$V_k = c(Z_k) = \sum_{i=0}^{k} p(Z_i) \quad (4)$$

where k = 0, 1, 2,…, L-1. Note that, S_k in equation (2) and V_k signify the CDFs of histograms of the IPI as well as the stated histogram respectively. In addition, the value of Z_k is found as:

$$Z_k = c^{-1}(S_k) \quad (5)$$

The S_k in Eq. (5) is similar as in HE and the preferred level Z_k is attained from Eq. (5). To summarize, HE is offered primary on the IPI histogram. Subsequently, the gathered gray levels are replotted to the obtainable gray levels in the stated histogram in order to attain HS. Fig. 1(b) exemplifies the stated histogram for the input histogram specified in Fig. 1(a). Nevertheless, there is no common rule obtainable to decide the most appropriate stated histogram.

IV. OPTIMIZED HISTOGRAM SPECIFICATION

The proposed Constrained Histogram Specification is an efficient scheme for improving the contrast of IPI. The OHS algorithm is specified as follows:

PROCEDURE OHS
Input : IPI Z(i, j), v, r
Output : OHSed Image
BEGIN

1. Calculate the PDF, $p(Z_q)$ for the input image Z
2. Compute M1=Median($p(Z_q)$)
3. Compute pu = v * max(PDF)
4. Assign pl=0.0001
5. Modify the PDF values as:
   IF ($p(Z_q) > p_u$)
   $pc(Z_q) = p_u$
   ELSE IF ($p(Z_q) <= pu$) AND ($p(Z_q) > p_l$)
   $$p_c(Z_q) = \left(\frac{p(Z_q) - p_l}{p_u - p_l} \right)^r * p_u$$
   ELSE
   $pc(Z_q) = p_l$
   ENDIF
6. Compute M_2 = Median($pc(Z_q)$)
7. Compute Median Adjustment Factor as, $M_f = |M_2 - M_1|$
8. Add Mf to the modified PDFs, $pc(Z_q)$
9. Apply Histogram Specification procedure to form OHSed Image
10. Return OHSed Image

END

The OHS procedure takes three constraints as input. Apart from the IPI which is input, Z (i ,j), v and r are the other two constraints that performance as scalability restrictions.

They show a foremost part in improving the contrast of the particular image. Both v and r accept values lies from 0.1 to 1.0. The determination of v is to clip the PDFs of greater values and that of r is to defend low frequently happening intensity values and control the occurrence of over enhancement. The median values of PDFs are established before and after modification as M1 and M2 respectively.

A median adjustment factor is estimated as the difference between M1 and M2 and is further added back to the modified PDFs to recompense for the luminance change. Lastly, the histogram specification is achieved to provide the resultant OHSed image. As the performance of the OHS depends on the v and r that are image-dependent, generalizing their optimality still remains as a challenge.

In order to identify the finest values for v and r, a MPSO scheme is utilized in which a fitness value is described to exploit the contrast enhancement of any IPI. Further, the numerous measures are implemented including Discrete Entropy (DE), Contrast Improvement Index (CII) that is employed to estimate the degree of image contrast improvement. It is established in this work where DE offers a superior trade off than CII. Therefore, DE will be designated as the fitness value. Moreover, CII is employed as an additional performance measure to compare the outcomes of OHS with other contemporary schemes.

Discrete Entropy (DE)

DE (Z) measures the fruitfulness of details in an image after improvement [12]. DE (Z) will be calculated as follows

$$DE(Z) = -\sum_{k=0}^{255} p(Z_q)\log_2(p(Zq)) \quad (6)$$

While the DE (Z) of an improved IPI which is nearer to IPI, it is said that the actualities of the IPI are well-maintained in the IPI.

Contrast Improvement Index (CII)

CII can be another numerical measure for IPI contrast improvement that can be definite as [13]:

$$CII = \frac{CVt}{CV_O} \quad (7)$$

where CVt and CVo denote the contrast values of the treated and the original IPI respectively. Let C denotes the contrast value of an IPI and it is evaluated as follows:

$$C = \frac{(f-b)}{(f+b)} \quad (8)$$

where f is the mean gray level of the IPI and b is mean gray level of the circumstantial. Larger CII values signify enhanced contrast.

Modified Particle Swarm Optimization (MPSO)

In the proposed model, MPSO is adopted to identify optimal values of 'v' and 'r'. MPSO method is population-based algorithm that employs a number of particles and it establishes a swarm patrol nearby in the search region observing for a superior result [16]. Every particle retains track of its values in the solution region that are related with the superior result. This significance is named personal best (pbest). The finest value which is chased through the MPSO is the finest value attained up to now through any agent in the neighbor area, and it is termed global best (gbest). Further, the simple idea of MPSO stays in moving every agent near its pbest and the gbest sites as exposed in Fig.2.

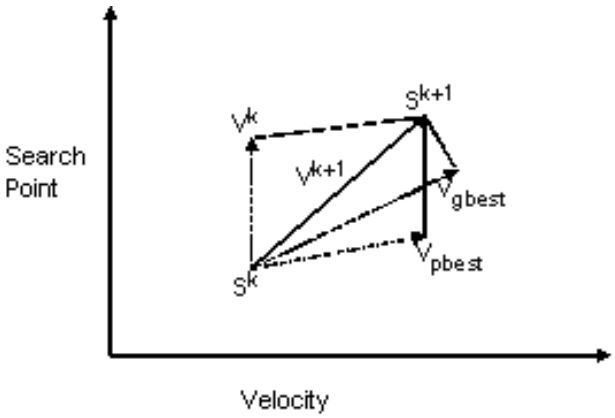


Fig. 2 Proposed MPSO searching point

S^k : present searching point.
S^{k+1} : changed searching point.
V^k : present velocity.
V^{k+1} : changed velocity.
V_{pbest} : velocity depends on pbest.
V_{gbest} : velocity depends on gbest

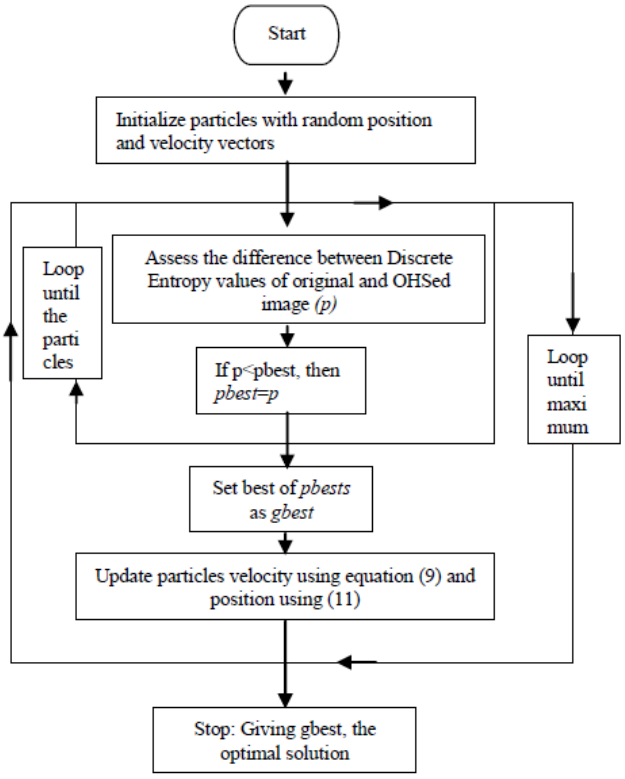


Fig. 3 Work Flow of proposed MPSO for OHS

Every particle modifies its site via the following statistics: the present sites, the present velocities, the distance between the present site and pbest, the distance between the present site and the gbest.

Every particle's velocity can be modified as follows.

$$V_i^{k+1} = wV_i^k + c_1 \times rand() \times (pbest_i - s_i^k) + c_2 \times rand() \times (gbest_i - s_i^k) \quad (9)$$

where, Vik is the velocity of particle i at iteration k (usually in the range 0.1 to 0.9); the c1 and c2 are in the range 0 to 4; rand() is the random number between 0 and 1; sik is present site of particle i at iteration k; w is inertia weight which is fixed to be in the range 0.1 to 0.9 and can be calculated as:

$$w = \frac{wMax - [(wMax - wMin) \times iteration]}{\max Iteration} \quad (10)$$

The particle's site can be updated by means of the modified velocity and it is given by:

$$S_i^{k+1} = S_i^k + V_i^{k+1} \quad (11)$$

The finest values of v and r are establish as presented in the Fig. 3. The fitness function p is computed as the dissimalarity between the Discrete Entropy standards of normal and OHSed image.

V. RESULTS AND DISCUSSION

In this technique, the value of 'v' for the evaluation of Pu and the power law index, 'r' are governing the improvement of contrast. The finest values for 'v' and 'r' are establish by means of MPSO algorithm. The fitness function is formulated to minimize the dissimilarity between the entropy values of the original and OHSed images. To assess the operation of the proposed technique, typical images like Airport, Einstein, F16, Truck, Pirate, Jet, Aircraft and U2 are selected. Fig. 4 shows the convergence graph for Truck image for the maximum velocity variation. It can be clearly shown from the graph that the optimal values of 'v' and 'r' are generated quickly (within 5 generations with less vMax). This is not only for Truck image, but for other images too. This substantiates the effectiveness of the OHS model and the same was witnessed for the remaining test images too.

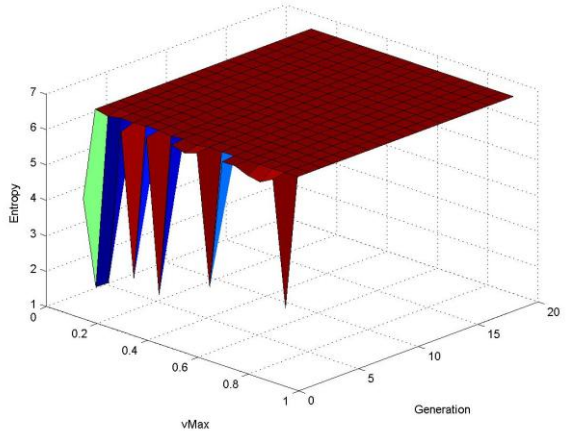


Fig. 4 Effect of vMax (Maximum Velocity)

The operation of OHS is quantitatively evaluated in terms of DE and CII that are calculated for those test IPI. These same measures are evaluated for existing HE approaches including GHE, BBHE, DSIHE, WTHE and HS and listed in Table 1 and Table 2 respectively for comparative analysis. It is apparent from Table 1 that the OHS model has larger entropy standards that are much nearer to those of the original IPI. This indicates that the proposed technique conserves the particulars of the normal IPI in the improved image. The CII values of the test IPI for numerous HE approaches and the OHS technique are demonstrated in Table 2. For all test IPI, OHS is having larger CII value compared with existing techniques.

Most the Histogram modification based enhancement techniques produce a shift in mean in the output image owing to the redeployment of intensity standards throughout intensity normalization. Though, OHS is proved to superior the IPI mean in the output.

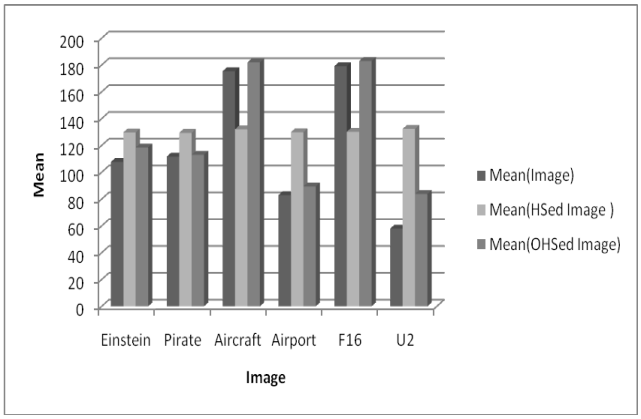
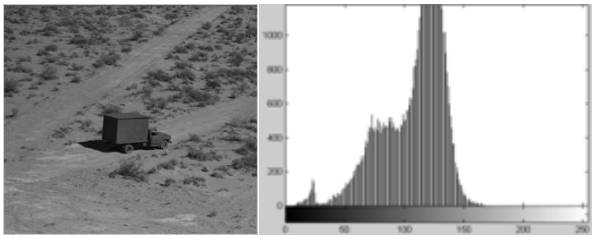


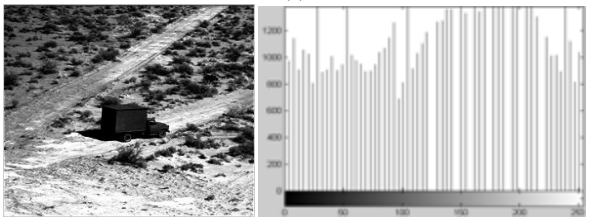
Fig. 5 Mean of Original, HSed and OHSed images

Table 1. Discrete Entropy values comparisons

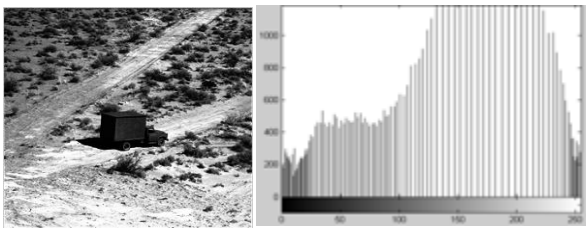
Method / Image	Original	GHE	BBHE	DSIHE	HS	WTHE	OHS (Proposed method)
Airport	6.7337	5.8853	6.6341	6.6279	6.6286	5.3907	6.7145
Einstein	6.8841	5.9436	6.7429	6.7226	6.7695	5.3766	6.882
F16	6.6744	5.7103	6.5717	6.5624	6.4533	5.9356	6.6406
Truck	6.5461	5.8041	6.4384	6.4204	6.4693	5.4722	6.5459
Pirate	7.3118	5.9842	7.2232	7.2223	7.2473	7.2569	7.3074
Jet	6.552	5.8116	6.3764	6.3257	6.3299	5.3287	6.5463
Aircraft	5.4316	5.0356	5.3019	5.2664	5.286	4.8541	5.4297
U2	6.5388	5.0128	5.5824	5.4874	5.4453	5.4921	5.6256



(a)



(b)



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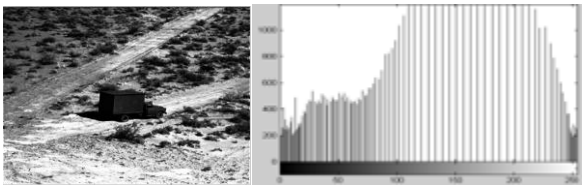
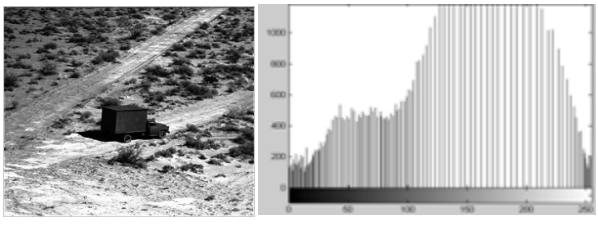
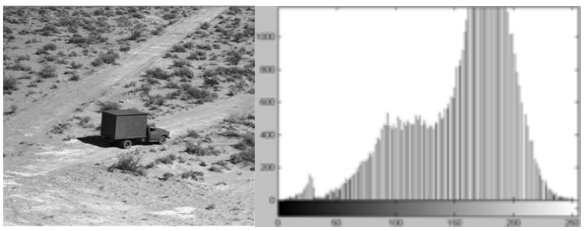


(d)

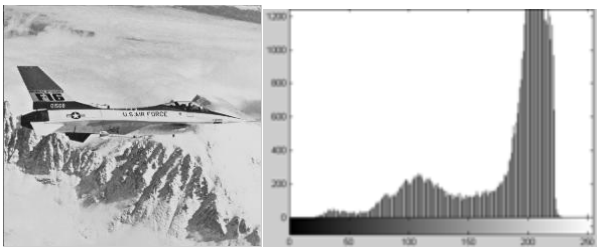


(e)

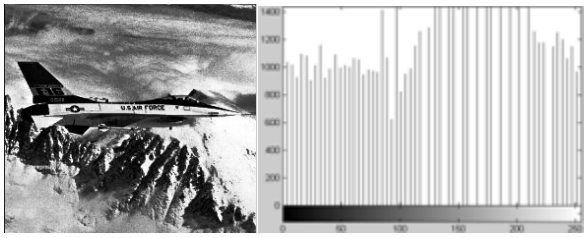


(f)

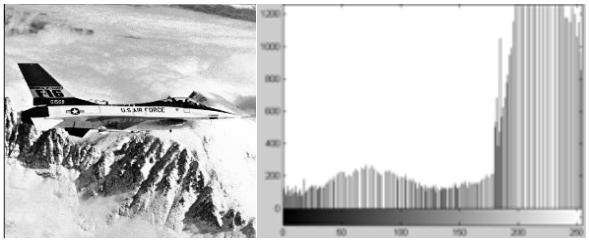
Fig. 6. (a) Initial Truck image and the resulting images of (b) HE (c) BBHE (d) DSIHE (e) WTHE (f) OHS



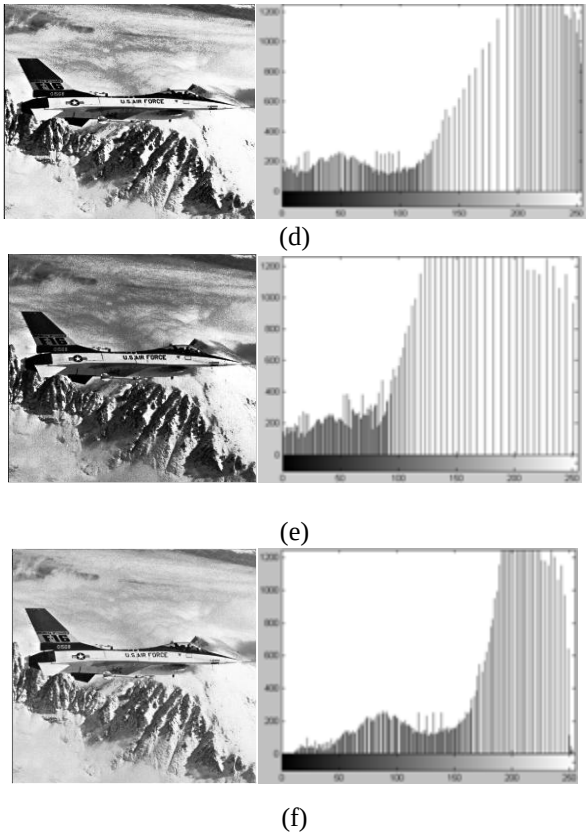
(a)



(b)



(c)



(d) (e) (f)

Fig. 7. (a) Initial F16 image and the resulting images of (b) HE (c) BBHE (d) DSIHE (e) WTHE (f) OHS

Table 2. Comparison of CII values

Method / Image	GHE	BBHE	DSIHE	HS	WTHE	OHS (Proposed method)
Airport	0.7324	0.7524	0.7748	0.7393	0.7653	0.8960
Einstein	0.9592	0.9829	0.9937	1.0356	0.8846	1.0928
F16	0.8323	0.8470	0.8465	0.8693	0.7417	0.9743
Truck	0.9217	0.9488	0.9253	0.9627	0.8282	1.0200
Pirate	0.6710	0.6813	0.6813	0.7001	0.9385	0.9865
Jet	0.6978	0.7011	0.6911	0.7044	0.6220	0.9393
Aircraft	0.7554	0.7270	0.7695	0.7446	0.7481	0.9304
U2	0.6897	0.6705	0.7048	0.7018	0.9461	0.8988

A comparative study among the mean values of the original, HSed and OHSed test images are carried out and is shown in Fig. 5. It is evident from above figure that HS radically changes the mean value of the IPI which has resulted in brightness degradation. Nevertheless, the well-ordered process of OHS provides mean values that are nearer to that of unique ones. This feature resulted in conserving the brightness of the IPI in the output.

The qualitative measure of the operation of OHS and those contemporary approaches is demonstrated by Truck and F16 images shown in Fig. 6(a) – 6(f) and Fig. 7(a) – 7(f). Fig. 6(b) – 6(e) and Fig. 7(b) – 7(e) are the improved images via the typical approaches like HE, BBHE, DSIHE and WTHE respectively. Moreover, it was seen from the above images that the typical approaches drastically change the unique characteristics of the IPI while improving the contrast. The results of contemporary methods shown in those figures have significant change in their brightness also. Such changes are clearly revealed by analyzing the corresponding histogram patterns of the images.

Fig. 6(f) and Fig. 7(f) are the outcomes of the OHS method in which the unique features of the IPI are well conserved as well as the corresponding stretched histogram patterns resembles the original histogram pattern of the input image which means that there exists controlled specification. Moreover, Fig. 6(f) and Fig. 7(f) clearly show that the pictorial insight of the proposed technique is superior to those of the existing models. Furthermore, the proposed technique yields superior outcomes for supplementary test IPI too.

VI. CONCLUSION

The average gray level of the IPI is dissimilar from that of the histogram equalized output image. The OHS model is evidenced to resolve the issue efficiently. The proposed technique also achieves the preferred intention of contrast enhancement of any specified IPI without removing the unique features of the IPI. It is computationally modest and is simple to execute. It offers reliability in contrast enhancement, by suitably regulating the constraints includes 'v' and 'r'. This technique may suitably be applied in the real time applications.

REFERENCES

1. Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing, 2nd ed., Prentice Hall, 2002
2. Kim, Y., Contrast enhancement using brightness preserving bi-histogram equalization, *IEEE Transactions on Consumer Electronics*, vol. 43, 1997, pp. 1-8.
3. Wan, Y., Chen, Q., Zhang, B., Image enhancement based on equal area dualistic sub-image histogram equalization method, *IEEE Transactions on Consumer Electronics*, vol. 45, 1999, pp. 68-75.
4. Chen, S., Ramli, A.R., Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation, *IEEE Transactions on Consumer Electronics*, vol.49, 2003, pp.1301-1309.
5. Chen, S., Ramli, A.R., Minimum mean brightness error bi-histogram equalization in contrast enhancement, *IEEE Transactions on Consumer Electronics*, vol. 49, 2003, pp.1310-1319.
6. Sim, K.S., Tso, C.P., Tan, Y.Y., Recursive sub-image histogram equalization applied to gray-scale images, Pattern Recognition Letters vol. 28, 2007, pp. 1209-1221.
7. Wang, Q., Ward, R.K., Fast image/video contrast enhancement based on weighted thresholded histogram equalization, IEEE Transactions on Consumer Electronics, vol. 53, 2007, pp. 757-764.
8. Shanmugavadivu P., Balasubramanian K., Image Inversion and Bi Level Histogram Equalization for Contrast Enhancement, International Journal of Computer Applications vol. 15, 2010, pp. 61-65.
9. Shanmugavadivu P., Balasubramanian K., Image Edge and Contrast Enhancement using Unsharp Masking and Constrained Histogram Equalization, Communications in Computer and Information Science vol. 140, 2011, pp. 129-136.
10. Kim, M., Chung, M.G., Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement, IEEE Transactions on Consumer Electronics, vol. 54, 2008, pp. 1389-1397.
11. Ibrahim, H., Kong, N.S.P., Image sharpening using sub-regions histogram equalization, IEEE Transactions on Consumer Electronics, vol. 55, 2009, pp. 891-895.

12. Chao Wang, Zhongfu Ye, Brightness preserving histogram equalization with maximum entropy: A variational perspective, IEEE Transactions on Consumer Electronics, vol. 51, 2005, pp. 1326-1334.
13. Yoon, J.H., Ro, Y.M., Enhancement of the contrast in mammographic images using the homomorphic filter method, IEICE Transactions on Information and Systems, E85-D(1), 2002.
14. Kennedy J., Eberhart, R., Particle swarm optimization, *IEEE International Conference on Neural Networks*, Vol..4, 1995, pp. 1942-1948.
15. A.Prasanth, and S.Pavalarajan, "Zone-Based Sink Mobility in Wireless Sensor Networks", *Sensor Review*, Vol. 39, no.6, 2019, pp. 874-880.
16. A. Prasanth, Pavalarajan.S, M.Karthihadevi, G.Sasi,"Particle Swarm Optimization Algorithm Based Zone Head Selection In Wireless Sensor Networks",*International Journal Of Scientific & Technology Research*, Vol.8(9), pp.1594-1597,2019.

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