A novel gamma correction approach using optimally clipped sub-equalization for dark image enhancement

H. Singh[a], N. Agrawal[b], A. Kumar[c], G.K. Singh[d] and H. -N. Lee[e]
[a,b,c]Indian Institute of Information Technology Design and Manufacturing Jabalpur, Jabalpur-482005, India
[c]Presently, Visiting Researcher, School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology, Gwangju, Korea
[d]Department of Electrical Engineering, Indian Institute of Technology, Roorkee-247667, India
[e]School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology, Gwangju, Korea
[a]himanshu.iiitj@gmail.com, [b]nikhil.agrawal.ec@gmail.com, [c]anilkdee@gmail.com, [d]gksngfee@gmail.com, [e]heungno@gist.ac.kr

***Abstract*—In this paper, an efficient statistical approach employing a highly adaptive gamma correction based on adaptively clipped and locally equalized histogram using mean-median statistical pair, is presented for the enhancement of low contrast dark images without losing their intrinsic features. For this purpose, linearly stretched intensity range segmentation, first based on median and mean distribution sub-histograms are derived for local equalization after optimal clipping. Later on, non-linear transformational mapping has been imposed by suitable gamma-correction using the required gamma value-set, which itself is derived by cumulative distribution of the intensity values in adaptively equalized histogram. The proposed methodology clearly outperforms the other state-of-the-art methods in terms of complexity as well as quantitative and qualitative performance; and hence, can be appreciably used for a wide and dynamic range of image-database belonging to various domains ranging from biomedical images to remotely sensed satellite images.**

Keywords- sub-exposure clipping; gamma correction; remotely-sensed images ; image quality enhancement.

I. INTRODUCTION

Contrast enhancement is highly desired for all kinds of human vision as well as machine vision digital imagery. The poor image acquisition capability and unbalanced illumination both leads to dark images, where mean level is so low that desired contrast enhancement without losing intrinsic features is always very challenging task. Similarly, remotely sensed images of the earth's surface and its atmosphere, when captured through various kinds of sensors from a large distance in absence of desired and balanced natural light illumination, are mostly acquired as very dark and low contrast images [1]. Remotely sensed images are employed for geoscience studies, astronomy and geographical information systems; and hence, directly related to human welfare. As large amount of information lies in a very dense manner, in remotely sensed images, the prime objective is to preserve all the features during enhancement. Various kinds of spatial as well as transform-domain image contrast enhancement methodologies [2-5] have been proposed, but histogram based techniques have become very popular due to not so complex behavior of them. Various global as well as local histogram based techniques [6-8] have been proposed, but as obvious, all kind of local image features cannot be preserved by employing global techniques [9], due to which need for histogram sub-division arises; and hence, locally equalized histogram based enhancement approach has been proposed [10]. Locally modified histogram based techniques also leads to non-uniform enhancement, and leads to unnatural artifacts. Hence, uniform and more adaptive contrast enhancement is required. In this context, brightness preserving bi-histogram equalization (BBHE) [11], and then dualistic sub image histogram equalization (DSIHE) [12] has been proposed which excels due to median based division. Afterwards, mean brightness preservation using absolute mean brightness error (AMBE) and histogram division process, which yields minimum AMBE value [13] has been reported. Later on, recursive separation [14] along with BBHE is imparted. Similarly, recursive sub-image histogram equalization (RSIHE) [15] divides the histogram based on median, instead of its mean value. Still, it was very challenging to decide the basis of histogram division; and hence, an extension of dynamic histogram equalization (DHE) using Gaussian-smoothing filtering has been proposed for better enhancement [16]. In the same context, brightness preserving dynamic fuzzy histogram equalization (BPDFHE) [17] was proposed, but not found suitable for dark image enhancement. Further improvement has been imposed by quadrants dynamic histogram equalization (QDHE) [18] by histogram division, based on median along with mean based exposure clipping. Dynamic quadrants histogram equalization plateau limit (DQHEPL) [19], bi-histogram equalization median plateau limit (BHEPL-D) [20], exposure based sub image histogram equalization (ESIHE) [21] and median-mean based sub-image-clipped histogram equalization (MMSICHE) [22] have been also proposed using various clipping as well as subsequent sub-image equalization strategies. Above methodologies are somehow efficient for contrast enhancement for general images, but for much better dark image enhancement, gamma correction has been also proposed where redistribution of dynamic intensity range is carried out by properly specifying the gamma parameter. Here, enhancement has been imparted by varying gamma (γ) parameter. Some intelligence for applying gamma correction has been also imparted using a robust approach termed as adaptive gamma correction with weighting distribution (AGCWD) [24]. Transform-domain sub-band decomposed gamma correction along with gamma tuning has been also proposed [25, 26]. In this paper, more adaptive approach has been proposed for overall quality enhancement for dark and low contrast images along with contrast as well as entropy enhancement without losing their intrinsic features.

II. PROBLEM FORMULATION

For imparting proper contrast enhancement, pixel intensity values can be mapped on non-linearly so that standard deviation can be sufficiently increased for the corresponding intensity value set along with some amount of positive mean-shift, which is extremely significant for increasing its dynamic range for proper contrast enhancement. Here, gamma-value set (which consists of 256 or 2^8 distinct values) has been evaluated directly from the cumulative distribution obtained from mean-median based sub-equalized and optimally clipped histogram; and hence, proper avoidance of all kind of artifacts can be done as properly balanced and contrast enhanced histogram. Hence, three levels of intelligence have been imparted here. First, optimal histogram segmentation has been imparted which is followed by optimal histogram clipping. At last, subsequently equalized histogram is itself used to derive the required gamma value-set. Hence, transformational mapping can be derived as:

$$T(l) = (l)^{\gamma(l)} = (l)^{1-cdf(l)}, \tag{1}$$

Here, l stands for the normalized input intensity values ranging from 0 to 1. The intensity transformation is then obtained by using above equation. Previously, deciding a most suitable value of gamma adaptively is a very tedious task; as a very slight variation in the value for gamma may cause a very significant variation. Huang *et al.* [24] has proposed an approach by directly utilizing the cumulative distribution function to derive a normalized gamma function for this purpose. In this paper, a similar kind of methodology has been employed with a very effective improvement along with more adaptive nature, which results in an obvious outperformance as well. Here, mean-median based adaptively sub-equalized and optimally clipped histogram in place of original input histogram itself unlike that was proposed previously; and hence, due to this, weighting distribution is not required as well, which in turn counters for somehow seemingly increased complexity up to certain extent. Hence, the trade-off between complexity as well as performance has been also maintained as well.

III. PROPOSED METHEDOGOLY

The prime objective is to enhance the quality of dark and low contrast images, along with suitable increment in the information content. Enhancement can be directly imposed in case of gray-scale images, but for color image enhancement, HSV color model can be used; and hence, the chromatic and non-chromatic information can be easily decoupled using this model. Likewise, for multispectral images, each band should be processed individually in a similar manner. The contrast of color images can be efficiently enhanced only by enhancing the luminance values keeping hue and saturation values preserved, after employing linear contrast stretching. Hence, only histogram $h(i)$ of luminance part has been used for further processing, can be represented as:

$$h(i) = \{n(i)\}, \tag{2}$$

Here, $n(i)$ represents the pixel-count having i^{th} intensity value. Histogram-division has been performed using median intensity value I_m so that the two sub-histograms having equal bin values can be efficiently derived out of it as:

$$h_{lo}(i) = \{h(i) | 0 \le i \le I_m\}; \tag{3}$$

$$h_{hi}(i) = \{h(i) | I_m < i \le L-1\}, \tag{4}$$

Each sub-histogram has been further sub-divided using their individual mean intensity values for maintaining globally balanced segmentation; and hence, four sub-histograms are:

$$h_1(i) = \{h_{lo}(i) | 0 \le i \le I_{\mu 1}\}; \tag{5}$$

$$h_2(i) = \{h_{lo}(i) | I_{\mu 1} \le i \le \mathrm{I}_m\}; \tag{6}$$

$$h_3(i) = \{h_{hi}(i) | I_m \le i \le \mathrm{I}_{\mu 2}\}; \tag{7}$$

$$h_4(i) = \{h_{hi}(i) | I_{\mu 2} \le i \le L-1\}; \tag{8}$$

Global histogram clipping has been employed by using optimal clipping limit decided by the minimum value out of mean and median bin-value count for histogram, when calculated globally. CDFs are evaluated for all sub-histograms as:

$$c_j(i) = \frac{1}{N_j}\sum_{k=0}^{i} h_j(k); \tag{9}$$

Here, N_j is the net pixel count in j^{th} sub-histogram. Equalize all sub-histograms (i.e. for j=1 to 4) independently as:

$$\tilde{I}_j = I_{j\_\min} + \left(I_{j\_max} - I_{j\_min}\right) * c_j(i), \tag{10}$$

Obtain the overall equalized image as:

$$\tilde{I} = \tilde{I}_1 \cup \tilde{I}_2 \cup \tilde{I}_3 \cup \tilde{I}_4, \tag{11}$$

Afterwards, cumulative distribution has to be derived for the above mentioned optimally clipped sub-equalized image so that the adaptive gamma value-set can be derived as:

$$\gamma(i) = 1 - cdf_m(i), \tag{12}$$

Finally, the enhanced output is achieved following Eq. (1), as:

$$I_{en}(i) = \left[\tilde{I}(i)\right]^{\gamma(i)}, \tag{13}$$

Thus, enhanced luminance ($\hat{V}$) channel output is also achieved from the above mapping combined with hue (*H*) and saturation (*S*) channel and reconverted back to RGB color space. Thus, overall adaptive image enhancement can be attained without any iterative and complex nature of the proposed approach; it can be also employed by real-time systems and also for video quality enhancement as well.

IV. EXPERIMENTATION AND RESULT ANALYSIS

In this section, the results have been illustrated for qualitative as well as quantitative evaluation. Some very popular performance indices like mean (μ), variance (σ^2), entropy (E) and gradient (G) of the image that indicates average brightness, average contrast, average information content and average sharpness of the image respectively, have been used here for reliable performance evaluation of the proposed approach and its comparison with other state-of-the-art methodologies. Mean brightness can be evaluated as [23]:

$$\mu = \frac{1}{M*N}\sum_{m=1}^{M}\sum_{n=1}^{N} I(m,n), \tag{14}$$

Here, the pixel intensity value $I(m,n)$ located at m^{th} row and n^{th} column of the equivalent M by N image matrix. Intensity variance or average contrast, which is deviation of the image intensity values from mean intensity level of the image, can be evaluated as [23]:

$$\sigma^2 = \frac{1}{M*N}\sum_{m,n} I_{en}(m,n)^2 - \left(\frac{1}{M*N}\sum_{m,n} I_{en}(m,n)\right)^2, \tag{15}$$

It takes into account the average intensities and their spread around the central pixel intensity value. Its higher value represents higher contrast, which is the prime objective here. The average information content or entropy value for a gray scale image can be evaluated as [23]:

$$E = -\sum_{i=0}^{I_{max}} p_i \, log_2(p_i), \tag{16}$$

Here, $p_i = n_i/(M*N)$ is the occurrence probability of i^{th} intensity level, and I_{max} is the maximum intensity value present in the image. Here, M*N symbolizes total pixel count of the M by N image under consideration. Similarly, the average color-information/entropy can be also calculated. The gradient is obtained from [26]:

$$G = \frac{1}{M*N}\sum_{x,y}\left(\Delta x^2 + \Delta y^2\right), \tag{17}$$

Here, $\Delta x = I_{en}(x,y) - I_{en}(x+1,y); \Delta y = I_{en}(x,y) - I_{en}(x,y+1);$ are the local gradients of enhanced image. Higher gradient value symbolizes more image sharpness for both human as well as machine vision systems, which is highly desired for a pleasant visualization. A rigorous experimentation has been performed along with reimplementation of various well-known and highly appreciated contrast enhancement methodologies such as GHE [23], knee-gamma correction based on DWT [25], AGCWD [24] and linearly stretched MMSICHE [22] for overall performance evaluation and comparison. Quantitative comparison for various satellite as well as non-satellite images [27-30] has been enlisted in Table I. In the same context, visual and qualitative analysis is explicitly presented in Fig.1. The explicit outperformance of this approach in terms of entropy as well as contrast values, which is highly desired for human vision as well as machine vision systems, can be easily found in Fig. 1 and Table I. For clear contrast evaluation for dark images, some amount of brightness enhancement is also desired which is also present here. Image sharpness content is also enhanced up to certain extent which is also desired.

Table I. Quantitative evaluation with comparison among input images, GHE [23], DWT based Knee Transformed Gamma Correction [25], AGCWD [24], RGB stretched MMSICHE [22] and proposed approach using performance indices such as Mean Brightness (μ), Contrast (σ^2), Entropy (E) and Gradient/Sharpness (G).

S.No.	Input Image	GHE [23]	DWT KNEE Gamma [25]	AGCWD [24]	Linearly stretched MMSICHE [22]	Proposed
1.	μ = 0.1909	μ = 0.6009	μ = 0.2413	μ = 0.3513	μ = 0.2634	**μ = 0.4667**
	σ^2= 0.0332	σ^2= 0.0595	σ^2= 0.0702	σ^2= 0.0703	σ^2= 0.0489	**σ^2= 0.1059**
	E = 6.2581	E = 5.5817	E = 6.3289	E = 6.8278	E = 6.5620	**E = 7.0039**
	G = 0.4802	G = 0.9146	G = 0.6386	G = 0.8714	G = 0.5912	**G = 1.1066**
2.	μ = 0.1060	μ = 0.6187	μ = 0.1402	μ = 0.2254	μ = 0.1645	**μ = 0.4463**
	σ^2= 0.0076	σ^2= 0.0390	σ^2= 0.0220	σ^2= 0.0524	σ^2= 0.0184	**σ^2= 0.0954**
	E = 5.5645	E = 5.4128	E = 5.9575	E = 5.3702	E = 5.9273	**E = 6.7227**
	G = 0.2513	G = 0.5835	G = 0.3700	G = 0.7053	G = 0.3983	**G = 1.0528**
3.	μ = 0.2232	μ = 0.6124	μ = 0.2765	μ = 0.3463	μ = 0.2763	**μ = 0.4908**
	σ^2= 0.044	σ^2= 0.0472	σ^2= 0.0828	σ^2= 0.0815	σ^2= 0.0777	**σ^2= 0.1371**
	E = 5.9635	E = 5.0862	E = 6.1624	E = 6.1137	E = 6.1428	**E = 6.2828**
	G = 0.6581	G = 0.7123	G = 0.8379	G = 0.9571	G = 0.7954	**G = 1.2647**
4.	μ = 0.3519	μ = 0.6391	μ = 0.4953	μ = 0.5207	μ = 0.4701	**μ = 0.6577**
	σ^2= 0.0094	σ^2= 0.0622	σ^2= 0.0389	σ^2= 0.0313	σ^2= 0.0341	**σ^2= 0.0682**
	E = 6.8800	E = 5.8622	E = 7.4347	E = 7.3007	E = 7.3374	**E = 7.5638**
	G = 0.2415	G = 0.5648	G = 0.4748	G = 0.4318	G =0.4341	**G = 0.6276**
5.	μ = 0.1893	μ = 0.6362	μ = 0.2173	μ = 0.3284	μ = 0.2342	**μ = 0.4740**
	σ^2= 0.0327	σ^2= 0.0409	σ^2= 0.0636	σ^2= 0.0712	σ^2= 0.0503	**σ^2= 0.1229**
	E = 5.7253	E = 5.0644	E = 5.8603	E = 6.0365	E = 5.8950	**E = 6.2021**
	G = 0.3724	G = 0.4500	G = 0.4706	G = 0.5874	G = 0.4619	**G = 0.7797**
6.	μ = 0.2761	μ = 0.5849	μ = 0.3777	μ = 0.4449	μ = 0.3651	**μ = 0.6120**
	σ^2= 0.0228	σ^2= 0.0658	σ^2= 0.0619	σ^2= 0.0583	σ^2= 0.0419	**σ^2= 0.0966**
	E = 6.6138	E = 5.7501	E = 7.2006	E = 7.0882	E = 6.8710	**E = 7.2930**
	G = 0.2012	G = 0.3331	G = 0.3140	G = 0.3112	G = 0.2981	**G = 0.4031**
7.	μ = 0.2593	μ = 0.5923	μ = 0.3292	μ = 0.3969	μ = 0.3630	**μ = 0.5403**
	σ^2= 0.0422	σ^2= 0.0505	σ^2= 0.0933	σ^2= 0.0666	σ^2= 0.0657	**σ^2= 0.1079**
	E = 6.6918	E = 5.6414	E = 6.6326	E = 6.9417	E = 6.9062	**E = 7.1427**
	G = 0.4674	G = 0.5300	G = 0.6530	G = 0.6258	G = 0.6944	**G = 0.7975**
8.	μ = 0.3152	μ = 0.6245	μ = 0.4366	μ = 0.4808	μ = 0.6390	**μ = 0.6515**
	σ^2= 0.0289	σ^2= 0.0835	σ^2= 0.0685	σ^2= 0.0619	σ^2= 0.2307	**σ^2= 0.1022**
	E = 6.7738	E = 5.7949	E = 7.2808	E = 7.1817	E = 7.1586	**E = 7.3928**
	G = 0.2568	G = 0.5088	G = 0.3821	G = 0.3953	G = 0.4709	**G = 0.4970**

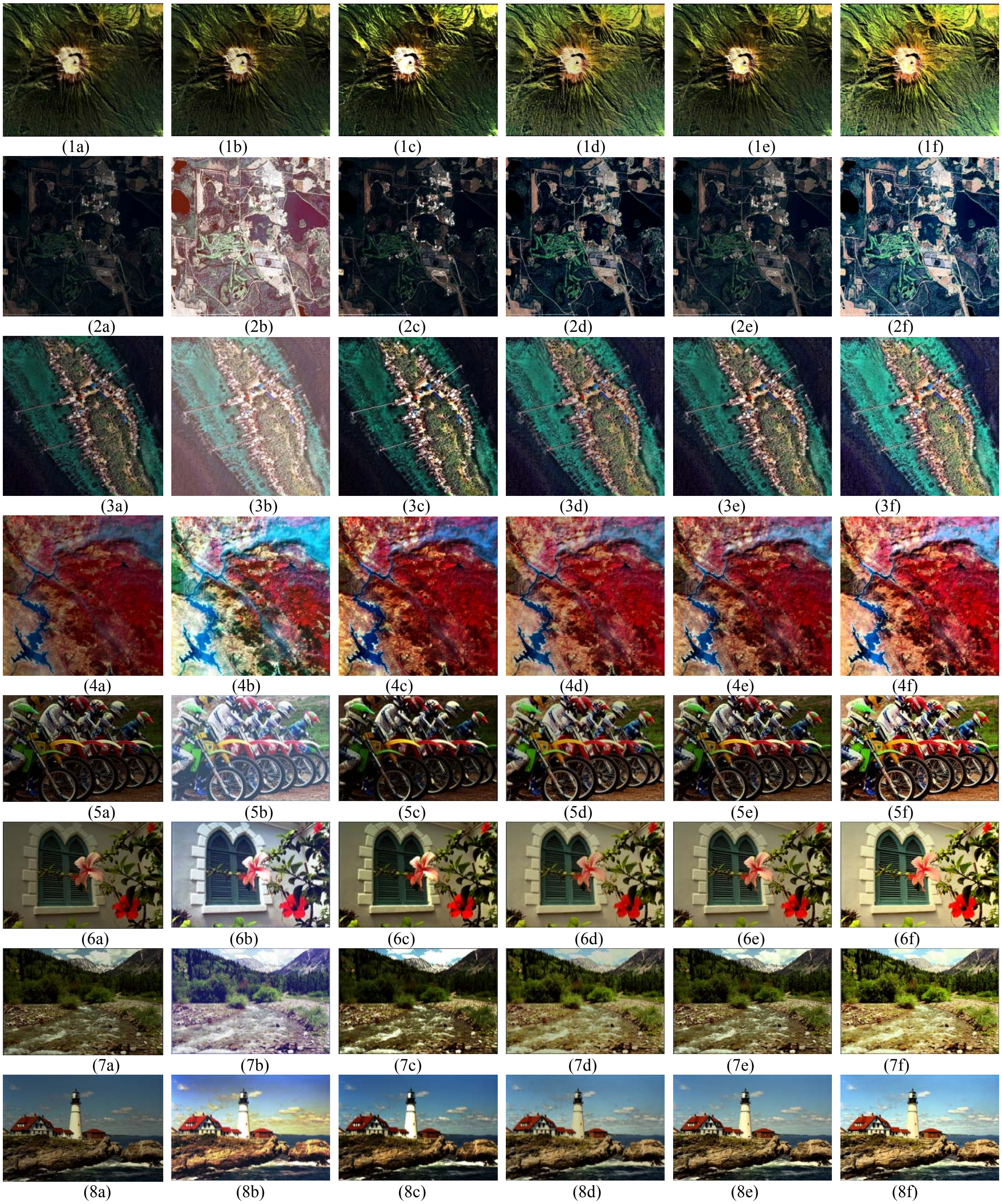

Fig. 1. Visual results and their comparison. Here, **1a-8a** are low contrast input images [27-30], **1b-8b** represent GHE [23] enhanced output images, **1c-8c** represent enhanced images using knee-gamma correction based on DWT [25], **1d-8d** represent AGCWD [27] enhanced output images, **1e-8e** represent enhanced images using linear stretched MMSICHE [22], and **1f-8f** represent enhanced output using proposed output.

V. Conclusion

In this paper, a novel and highly adaptive statistical, quality enhancement approach for very dark and low contrast satellite as well as non-satellite images has been developed so that more and more information can be acquired from the image captured. Contrast enhancement along with entropy as well as sharpness enhancement for almost all kind of dark images, is a desirable key feature of this approach; and hence, is equally applicable for human vision as well as machine vision systems. Also, due to absence of any kind of iterative approach, this approach is also time efficient, and can be easily employed with real-time image capturing as well as image enhancement systems. The desired performance has been achieved and measured by using performance metrics like mean (average brightness), variance (average contrast), entropy (average information content) and gradient (sharpness) of the image. In addition to it, the visual results also clearly indicate its superiority over existing methods with significant difference.

References

[1] Demirel, H., Ozcinar, C., Anbarjafari, G.: 'Satellite Image contrast enhancement using discrete wavelet transform and singular value decomposition'. IEEE Geoscience and Remote Sensing Letters 2010, 7(2), pp. 333–337.

[2] Arici, T., Dikbas, S., Altunbasak, Y.: 'A histogram modification framework and its application for image contrast enhancement', IEEE Trans. on Image Processing, 2009, 18, (9), pp. 1921-1935.

[3] Chang, Y.C., Chang, C.M.: 'A simple histogram modification scheme for contrast enhancement'. IEEE Trans. Cons. Elect., 2010, 56, (2), pp. 737-742.

[4] Polesel, A., Ramponi, G., Mathews, V.: 'Image enhancement via adaptive unsharp masking'. IEEE Trans. Image Process., 2000, 9, (3), pp. 505-510.

[5] Hanmandlu, M., Jha, D.: 'An optimal fuzzy system for colour image enhancement'. IEEE Trans. on Image Process., 2006, 15, (10), pp. 2956-2966.

[6] Kim, J.Y., Kim, L.S., Hwang, S.H.: 'An advanced contrast enhancement using partially overlapped sub-block histogram equalization', IEEE Transactions on Circuits System Video Technology, 2001, 11(4), pp. 475-484.

[7] Lamberti, F., Montrucchio, B., Sanna, A.: 'CMBFHE: a novel contrast enhancement technique based on cascaded multistep binomial filtering histogram equalization', IEEE Trans. Cons. Elect., 2006, 52, (3), pp. 966-974.

[8] Chen, Z.Y., Abidi, B.R., Page, D.L., Abidi, M.A.: 'Gray-level grouping (GLG): an automatic method for optimized image contrast enhancement-part I: the basic method', IEEE Transactions on Image Process., 2006, 15, (8), pp. 2290-2302.

[9] Abdullah-Al-Wadud, M., Kabir, M.H., Dewan, M.A.A., Oksam C.: 'A dynamic histogram equalization for image contrast enhancement'. IEEE Trans. Cons. Elect., 2007, 53, (2), pp. 593–600.

[10] Chen, Z.Y., Abidi, B.R., Page, D.L., Abidi, M.A.: 'Gray-level grouping (GLG): an automatic method for optimized image contrast enhancement-part-II: the variations.' IEEE Trans. on Image Process., 2006, 15, (8), pp. 2303-2314.

[11] Kim, Y.T.: 'Contrast enhancement using brightness preserving bi-histogram equalization', IEEE Trans. Cons. Elect., 1997, 43, (1), pp. 1-8.

[12] Wan, Y., Chen, Q., Zhang, B.M. 'Image enhancement based on equal area dualistic sub-image histogram equalization method', IEEE Trans. Cons. Elect., 1999, 45, (1), pp. 68-75.

[13] Chen, S.D., Ramli, A.R.: 'Minimum mean brightness error bi-histogram equalization in contrast enhancement'. IEEE Trans. Cons. Elect., 2003, 49, (4), pp. 1310-1319.

[14] Chen, S.D., Ramli, A.R.: 'Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation', IEEE Trans. Cons. Elect., 2003, 49, (4), pp. 1301-1309.

[15] Sim, K.S., Tso, C.P., Tan, Y.Y.: 'Recursive sub-image histogram equalization applied to gray scale images'. Pattern Recognition Letters, 2007, 28, (10), pp. 1209-1221.

[16] Ibrahim, H., Kong, N.S.P.: 'Brightness preserving dynamic histogram equalization for image contrast enhancement'. IEEE Trans. Cons. Elect., 2007, 53, (4), pp. 1752-1758.

[17] Sheet, D., Garud, H., Suveer, A., Mahadevappa, M., Chatterjee, J.: 'Brightness preserving dynamic fuzzy histogram equalization'. IEEE Trans. Cons. Elect., 2010, 56, (4), pp. 2475-2480.

[18] Ooi, C.H., Isa, N.A.M. Quadrants dynamic histogram equalization for contrast enhancement, IEEE Trans. Cons. Elect., 2010, 56, (4), pp. 2552-2559.

[19] Ooi, C.H., Isa, N.A.M.: 'Adaptive contrast enhancement methods with brightness preserving', IEEE Trans. Cons. Elect., 2010, 56, (4), pp. 2543-2551.

[20] Tan, T.L., Sim, K.S., Tso, C.P.: 'Image enhancement using background brightness preserving histogram equalization'. Electronics Letters. 2012, 48, pp. 155-157.

[21] Singh, K., Kapoor, R.: 'Image enhancement using exposure based sub image histogram equalization'. Pattern Recognition Letters, 2014, 36, pp. 10-14.

[22] Singh, K., Kapoor, R.: 'Image enhancement via Median-Mean Based Sub-Image-Clipped Histogram Equalization'. Optik-Int. J. for Light and Electron Optic, 2014, 125, (17), pp. 4646-4651.

[23] Gonzalez, R. C., Woods, R. E.: 'Digital Image Processing'. (NJ: Prentice Hall 2009).

[24] Huang, S.C., Cheng, F.C., Chiu, Y.S.: 'Efficient contrast enhancement using adaptive gamma correction with weighting distribution', IEEE Transactions on Image Process., 2013, 22, (3), pp. 1032-1041.

[25] Bhandari, A.K., Kumar, A., Singh, G. K.: 'Improved knee transfer function and gamma correction based method for contrast and brightness enhancement of satellite image'. AEU-Int. J. of Elect. and Comm., 2015, 69, (2), pp. 579-589.

[26] Singh H., Kumar A.: 'Satellite Image Enhancement using Beta Wavelet based Gamma Corrected Adaptive Knee Transformation.' IEEE Int. Conf. on Communications and Signal Processing, 2016, pp. 97-101.

[27] 'NASA Visible Earth: Home', http://visibleearth.nasa.gov/, accessed on 15 May 2016.

[28] 'WorldView-2 Satellite Imagery and Sensor Specifications | SATPALDA', http://www.satpalda.com/gallery/, accessed on 15 May 2016.

[29] 'CRISP - Centre for Remote Imaging, Sensing and Processing', http://www.crisp.nus.edu.sg/, accessed on 15 May 2016.

[30] 'True Color Kodak Images', http://r0k.us/graphics/kodak/, accessed on 15 May 2016.