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GLOBAL AND LOCAL CONTRAST ENHANCEMENT OF IMAGE BY SPATIAL ENTROPY

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***Abstract*— This paper proposes a novel algorithm, which enhances the low contrast input image by using the spatial information of pixels. This algorithm introduces new method to compute spatial entropy of pixels using spatial distribution of gray levels. This is different than the conventional methods, this algorithm considers the distribution of spatial locations of gray levels of an image instead of gray level distribution or joint statistics computed from gray levels of an image. For each gray level the corresponding spatial distribution is computed by considering spatial location of all pixels having the same gray level in histogram. From the spatial distribution of gray levels of an image entropy can be measured and create distribution which can be further mapped to uniform distribution function to achieve final contrast enhancement. This method achieves contrast enhancement of low contrast image without altering the image if the image's contrast is high enough. This algorithm considers transform domain coefficient weighting to achieve global and local contrast enhancement of the image. Experimental results shows that proposed algorithm produces better enhanced images than existing algorithms.**

***Index Terms*—Contrast enhancement, spatial entropy, image quality enhancement, discrete cosine transform.**

I. Introduction

This Contrast enhancement is used to increase the contrast of an image with low dynamic range and bring out the image details that would be hidden [2]. The enhanced image is looks qualitatively better than the original image if the gray-level differences (i.e., the contrast) among objects and background are increased. Contrast enhancement is generally employed as a preprocessing for majority of image processing and in computer vision algorithms.

In general, it is difficult to design a visual artifact free contrast enhancement method. Considering this, we propose a global, computationally efficient spatial contrast enhancement method which performs enhancement by considering the spatial locations of gray-levels of an image instead of direct use of gray-levels or their co-occurrences. The mutual information between spatial location and distribution of gray levels of an image are used to obtain distribution function which is further mapped to uniform distributive function to achieve contrast enhancement.

The proposed algorithm is named as "Spatial Entropy based Contrast Enhancement in DCT (SECEDCT)" which is generalization of SECE which perform both global and local contrast enhancement of image. SECE produces global contrast enhancement of an input image without altering the processed histogram with respect to the original histogram. SECE produces the results of contrast enhanced image without any apparent distortion on it. To achieve both global and local contrast enhancement, transform the coefficients of globally enhanced image with SECE using 2D-DCT (2D discrete cosine transform). Further coefficient weighted and apply inverse 2D-DCT (2D inverse discrete cosine transform) to obtain output image which is contrast enhanced globally and locally.

The paper organized as follows literature survey on related work is given in section II. Section III represents new definition of spatial entropy and introduce the proposed algorithm. Section IV presents the experimental results and section V concludes the paper.

II. RELATED WORK

Contrast enhancement algorithms can be categorised into two major groups according to the data domain they are applied to [2]: 1) Transform-domain algorithms; and 2) Image domain algorithms.

In this transform-domain algorithms input image can be decomposed into different sub bands and modify them globally or locally. In this algorithms the magnitude of desired frequency components image data [3] can be modified and enables simultaneous global and local contrast enhancement. The algorithms are computationally complex, and in order to avoid degrading the image, they require appropriate settings of the associated parameters. For example, the center-surround retinex [3]-[7] algorithm which is developed to achieve lightness and color constancy in images. Here constancy refers to the perception of color and lightness invariant to spatial and spectral illumination variations. The enhanced image has the advantage of compressed dynamic range and also color is independent of the spatial distribution of the scene illumination. Problem with the algorithm is enhanced image may include "halo" artifacts, especially along boundaries between large uniform regions. In [4]-[5], three different transform domain (discrete cosine transform) contrast enhancement algorithms are proposed: a) logarithmic transform histogram matching (LTHM), b) logarithmic transform histogram shifting (LTHS), and c) logarithmic transform histogram shaping using Gaussian distributions (LTHSG). In general, transform domain coefficients are modified according to a mapping of transform domain coefficient distribution to a target distribution and then inverse transform (inverse discrete cosine transform) is applied to obtain contrast enhanced image.

In LTHM, target distribution is obtained from transform domain coefficient distribution of histogram equalized input image. A shifted version of transform domain coefficient distribution of input image is used as a target distribution in LTHS and a Gaussian distribution with a mean and standard deviation is employed as a target distribution in LTHSG. The latter algorithms require selection of histogram shift parameter and mean and standard deviation of Gaussian distribution which requires computationally demanding process. LTHM is designed to mimic the ability of histogram equalization without suffering from the side effects of an over expansion of the dynamic range. This method has the distinct advantage of being incredibly quick with no built in recursion making it a simple and fast solution for image enhancement based on the transform histogram. However, since the histogram of global histogram equalized image in transform domain is used as a target histogram, one can still observe the visual artifacts caused from global histogram equalization. Second-generation wavelets are also used to produce enhanced images without "halo" artifacts. In edge-avoiding wavelets based contrast enhancement algorithm (EAW) [8], the wavelet coefficients in transform domain are modified and inverse transform is applied to obtain contrast enhanced images. The method achieves both global and local contrast enhancement at the same time with a proper parameter selection.

Although the transform-domain contrast enhancement algorithms have shown promising results in a variety of Problem domains, due to their computational, memory, and proper parameter setting requirements, image-domain contrast enhancement algorithms are widely used. The conventional approach to enhance the contrast in an image is to manipulate the gray-level of individual pixels according to a specified target histogram.

The most widely used image-domain contrast enhancement algorithm global histogram equalization (GHE) [1] in this cumulative distribution function (CDF) of input image histogram can be matched to uniform distribution function. This GHE utilizes the available dynamic range of the image, it tends to over-enhance the image if there are large peaks in the histogram, which leads to a harsh and noisy appearance of the enhanced image. Another one is Local histogram equalization (LHE) algorithms, in this a small window is used and slides over every image pixel sequentially and the histogram of pixels within the current position of the window is equalized. Which is computationally complex and sometimes it over-enhances some portion of the image and any noise, and may produce undesirable checker-board effects. Human visual system (HVS) is also used to alleviate artifacts of GHE and improve the perceived contrast. An image is segmented into three regions using a HVS-based thresholding and image equalization is applied to each segment. Processed regions are combined with a weighting to create the final enhanced image. The algorithm's thresholding and merging stages depend on several thresholds which must be carefully selected by a visual observer and/or by local minima of a contrast measure of the output image with respect to the parameters. The parameters all are real valued and it is computationally demanding to select them which makes the algorithm impractical to be applied.

GHE assumes that the target histogram is uniformly distributed by changing the histogram specification. However, GHE fails in providing an efficient histogram specification. In the Exact histogram specification (EHS) the histogram of the image obtained after enhancement is almost exactly the desired one and histogram which is mostly considered as uniform. It is not sure that the output will be free of visual artifacts. The original image histogram is modified by weighting and thresholding before the histogram equalization in. The weighting and thresholding are performed by clamping the original image histogram at an upper threshold and at a lower threshold, and transforming all the values between these thresholds using a normalized power law function with an index. We refer the algorithm as weighted thresholded histogram equalization (WTHE) [9]. WTHE provides satisfactory enhancement with the carefully selected default parameter setting. Contrast enhancement in histogram modification framework (HMF) minimizes a parametrized cost function to compute a target histogram. The cost function is composed of penalty terms of minimum histogram deviation from the original and uniform histograms, and histogram smoothness. Furthermore, the edge information is embedded into the cost function to weight pixels around region boundaries to address noise and black/white stretching. Different parameter settings will result in different contrast enhancement. Similar to WTHE, adaptive gamma correction with weighting distribution (AGCWD) modifies the input histogram by weighting distribution and enhances image automatically using gamma correction, however, the algorithm may result in loss of details on bright regions of image when there are high peaks in the input histogram

III. SPATIAL ENTROPY BASED CONTRAST ENHANCEMENT IN DCT

A. Spatial entropy based contrast enhancement (SECE)

1. Consider an input image, X={x (i, j) | 0≤ i ≤H-1, 0≤ j ≤W-1} of size H×W pixels, assume that X has a dynamic range of $[x_d, x_u]$ where x (i, j) € $[x_d, x_u]$. The objective of the spatial entropy based contrast enhancement (SECE) is to generate naturally looking enhanced image, Y={y (i, j) | 0≤ i ≤H-1, 0≤ j ≤W-1} which has better visual quality than X. The dynamic range of Y can be stretched or compressed into interval $[y_d, y_u]$, where y(i, j) € $[x_d, x_u]$.$y_d < y_u$. In this work, the enhanced image utilizes the entire dynamic range. e.g for an 8 bit image $y_d = 0$ and $y_u = 255$.

2. Computation of spatial histogram of gray level of an image

Let $\chi = \{x_1, x_2, x_3 \dots\dots\dots, x_K\}$ be the sorted set of all possible K gray levels that exist in the input image X where $x_1 < x_2 < x_3 \dots\dots\dots < x_K$ where K is the number of distinct gray levels. The 2D spatial histogram of the gray level x_K on the spatial grid of X is computed as

$$h_k = \{h_k(m,n) \mid 1 \le m \le M, 1 \le n \le N\}, \quad (1)$$

Where m, n $\in Z^+$, $h_k(m,n) \in [0, Z^+]$ is the number of occurrence of gray level of an image in spatial grid located in the image region of $[(m\text{-}1)\frac{H}{M}, m\frac{H}{M}] \times [(n\text{-}1\frac{W}{N}, n\frac{W}{N})]$. The total number of grids on 2D histogram is MN which is dynamically estimated using the number of distinct gray levels K and aspect ratio $r = \frac{M}{N} = \frac{H}{W}$, i.e.,

$$M = (Kr)^{1/2}\ ;\ N = (\tfrac{K}{r})^{1/2}, \quad (2)$$

Here M, N are the integers. In forming 2D spatial histogram h_k of gray level x_k the aspect ratio of original image is protected on spatial grid. In the forming of a 2D spatial histogram spatial characteristics of pixels are protected.

3. Computation of spatial entropy and distribution function

Entropy is computed for gray level x_K can be represented as S_K. It can be computed using 2D spatial histogram h_K according to eq(3)

$$S_k = -\sum_{m=1}^{M}\sum_{n=1}^{N} h_k(m,n)\log_2(h_k(m,n)), \quad (3)$$

Which is used to compute discrete function f_k according to equation (4)

$$f_k = \frac{s_k}{\sum_{l=1, l\neq k}^{K} s_l}, \quad (4)$$

The discrete function f_k measures the relative importance of the gray level x_k with respect to the rest of gray levels x_l $l \neq k$, l= 1,2,…….K. The discrete function f_k further normalized according to equation (5)

$$f_k \leftarrow \frac{f_k}{F_k} = \frac{f_k}{\sum_{l=1}^{K} f_l}, \quad (5)$$

Where F_k is the cumulative discrete function defined as follows

$$F_k = \sum_{l=1}^{k} f_l, \quad (6)$$

Using the above cumulative distributive function F_k, x_k is mapped to y_k according to equation (7)

$$y_k = \lfloor F_k(y_u - y_d) + y_d \rfloor, \quad (7)$$

SECE designed for global contrast enhancement, thus single transfer function applied to entire image. The algorithm provides contrast enhancement without distortion. Proposed algorithm SECEDCT employ both SECE for global contrast enhancement and 2D-DCT for local contrast enhancement. The algorithm comprised of following steps as shown in figure (1). Apply SECE to the input image and enhance globally; for the globally enhanced image apply 2D-DCT; the transform domain coefficients are weighting; and apply inverse 2D-DCT and produce an output image.

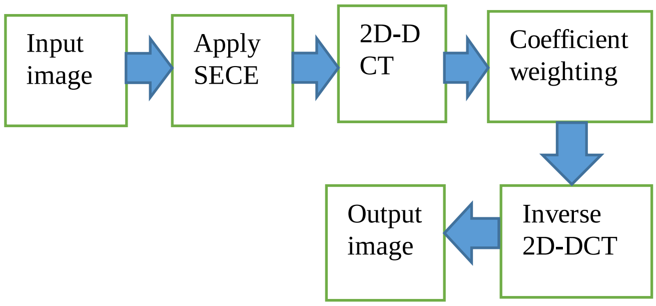

Fig 1: Block diagram of SECEDCT algorithm

The algorithm SECEDCT performs its operation on 2D-DCT [2], algorithm first applies global contrast enhancement using SECE which is followed by 2D-DCT transform.

B. Two dimensional discrete cosine transform

Consider the 2D-DCT of an image X={x (i, j) | 0≤ i ≤H-1, 0≤ j ≤W-1} produces a transform image D= {d (k, l) | 0≤ k ≤H-1, 0≤ l ≤W-1} of same size where

$$d(k,l) = C_k C_l \sum_{i=0}^{H-1}\sum_{j=0}^{W-1} x(i,j)\cos\left(\frac{\pi(2i+1)k}{2H}\right)\cos\left(\frac{\pi(2j+1)l}{2W}\right) \quad (8)$$

Where C_k and C_l are defined as

$$C_k = \begin{cases} \sqrt{\frac{1}{H}}, & k = 0 \\ \sqrt{\frac{2}{H}}, & 1 \le k \le H-1 \end{cases} \qquad C_l = \begin{cases} \sqrt{\frac{1}{W}}, & l = 0 \\ \sqrt{\frac{2}{W}}, & 1 \le l \le W-1 \end{cases} \quad (9)$$

The lower values of indices k and l refer to lower frequency components and vice versa. In order to increase the Local contrast of an image, higher frequency transform coefficients should be increased. Thus, the transform domain coefficients d (k, l) are modified according to

$$\hat{d}(k,l) = w(k,l)\, d(k,l) \quad (10)$$

Where the Weighting coefficient w (k, l) ∈ R defined as equation (11) which allocates higher coefficients for higher frequencies and vice versa.

$$w(k,l) = \left(1 + \frac{\alpha-1}{H-1}k\right)\left(1 + \frac{\alpha-1}{W-1}l\right) \quad (11)$$

Where $\alpha \ge 1.0$ is the level of enhancement. The higher the value of α, the higher the local contrast enhancement is. The higher the values of α also result in saturation on pixel values. The automatic selection of α is important it can be evaluated using the entropy using equation (5)

$$\alpha = \left(\sum_{k=1}^{K} f_k \log_2(f_k)\right)^{\gamma} \quad (12)$$

Where $\gamma \in [0, 1]$ determines the level of local contrast enhancement. After transform domain coefficients are weighted according to equation (10), the inverse 2D-DCT transform [1] is applied to obtain the globally and locally enhanced image Y={y (i, j) | 0≤ i ≤H-1, 0≤ j ≤W-1}

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$$y(i,j) = \sum_{k=0}^{H-1}\sum_{l=0}^{W-1} C_k C_l \hat{d}(k,l) \cos\left(\frac{\pi(2i+1)k}{2H}\right)\cos\left(\frac{\pi(2j+1)l}{2W}\right)$$

(13)

SECEDCT is generalized version of SECE as when $\alpha = 1$, i.e., $\gamma = 0$, is selected, w (k, l) becomes 1 for all *(k,l)*, and transform domain coefficients remain unchanged. Thus, SECEDCT will produce an output image which is the same as of the input image which is nothing but image enhanced by SECE algorithm. In other words, $\gamma = 0$ means global but no local enhancement.

IV. EXPERIMENTAL RESULTS

We are using natural test images that are taken from the Berkelay image dataset [10] to evaluate and compare SECEDCT with SECE and GHE, both qualitatively and quantitatively. It is not easy to assess the enhancement of image. Here the contrast of image can be measured by using one metric Expected measure of entropy by gradient (EMEG). One more metric we are evaluated is Gradient magnitude similarity deviation (GMSD) with this we are evaluating the perceptual similarity of original and enhanced image. GMSD is used to assess the quality of the image.

Expected measure of entropy by gradient (EMEG) [6] can be computed for an image X is computed as follows. Let image can be divided into $k_1 k_2$ over lapping sub blocks $X_{i,j}$ of size $w_1 \times w_2$ and EMEG of image X can be computed using below equation.

$$\text{EMEG(X)} = \frac{1}{k_1 k_2}\sum_{i=1}^{k_1}\sum_{j=1}^{k_2}\frac{1}{\beta}\max\left(\frac{x_{i,j}^{dx,h}}{x_{i,j}^{dx,l}+\epsilon}, \frac{x_{i,j}^{dy,h}}{x_{i,j}^{dy,l}+\epsilon}\right) \quad (14)$$

where *EMEG* (**X**) ∈ [0, 1], max *(・)* is a function to find the maximum of its operands, $X_{i,j}^{dx,h}$ and $X_{i,j}^{dx,l}$ are respectively, the maximum and minimum value of absolute valued derivative in *x*-direction of block **X**i, j and $X_{i,j}^{dy,h}$ and $X_{i,j}^{dy,l}$ are respectively, the maximum and minimum value of absolute valued derivative in *y*-direction of block **X**i, j, $\beta = 255$ is a weighting coefficient, ϵ is a constant used to prevent division by zero. A different block size (i.e., w1 ×w2) results in different EMEG value, and we use $w1 \times w2 = 8 \times 8$. High contrast sub-blocks give a high *EMEG* value, while for homogeneous sub-blocks the EMEG value should be close to zero. It is worth to note that *EMEG* is highly sensitive to noise. Here EMEG of SECEDCT output image is much more than then the EMEG of SECE and GHE output images.

Gradient magnitude similarity deviation (GMSD) [10] is measure of perceptual similarity of original and enhanced image. Image gradients are highly sensitive to distortion. For digital image gradient magnitude is defined as root mean square of image directional gradient along two orthogonal directions. The image gradient is computed by convolving image with linear filters such as the classic, sobel, prewitt filter. GMSD of an image can be measured using below equations.

$$\text{GMSD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\text{GMS}(i) - \text{GMSM})^2} \quad (15)$$

$$\text{GMSM} = \frac{1}{N}\sum_{i=1}^{N}\text{GMS}(i) \quad (16)$$

Where N is the total number of pixels in image, and GMSM represents gradient magnitude similarity mean which is computed from GMS (gradient magnitude similarity) of all the pixels of image. The lower the GMSD value less the distortion between original and enhanced image .GMSD value of SECEDCT enhanced image is much smaller than the enhanced images of SECE and GHE. SECEDCT algorithm quantitatively produce better results than SECE and GHE algorithms.

For qualitative evaluation we are taken the test image set of family and image set of couple at different level of contrast. Here we are taken four levels of contrast images in the decreasing order of contrast and applied to GHE, SECE and SECEDCT algorithms. The corresponding metrics of EMEG and GMSD are noted in tabular column as shown in figures. Table 1 shows the results of processing family image and figure 2 shows the corresponding output images and different level of contrast of GHE, SECE, SECEDCT algorithms. In the table we can observe that EMEG of output of SECEDCT algorithm is greater than GHE and SECE algorithm from level 1 to level4. Observing the GMSD values of SECEDCT algorithm which is less than the both SECE and GHE algorithms. The GMSD of GHE algorithm is greater than 0.1. It is worth to note that when GMSD≥ 0.1 the distortion is visually noticeable and distracting. Table 2 shows the results of processing couple image and figure 3 shows the corresponding output images and different level of contrast of GHE, SECE, SECEDCT algorithms. The above results shown that comparing with SECE and GHE, SECEDCT quantitatively produces the better results and enhances image both globally and locally.

Table 2 shows that results of processing couple image and figure 3 shows the corresponding output images and different level of contrast of GHE, SECE, SECEDCT algorithms. In the table we can observe that EMEG of output of SECEDCT algorithm is greater than GHE and SECE algorithm from level 1 to level4. Observing the GMSD values of SECEDCT algorithm which is less than the both SECE and GHE algorithms. In figure 3 (a), (e), (i), (m) in column 1 represents the low contrast input sample images the contrast of images is decreasing from level1 to level4. (b), (f), (j), (n) in column 2 represents the GHE output images. (c), (g), (k), (o) in column 3 represents the SECE output images. . (d), (h), (l), (p) in column 4 represents the SECEDCT output images.

A. Figures and Tables

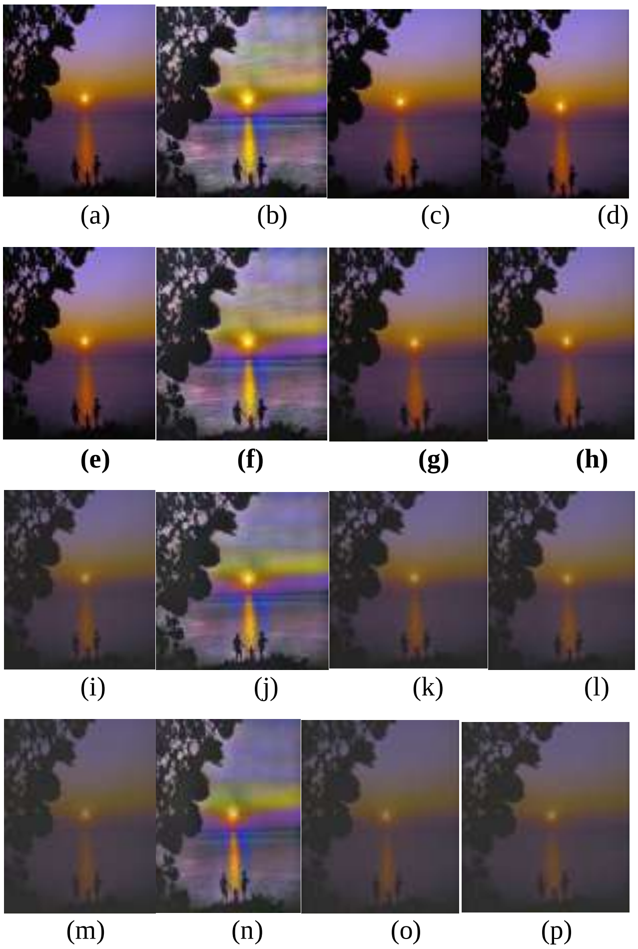


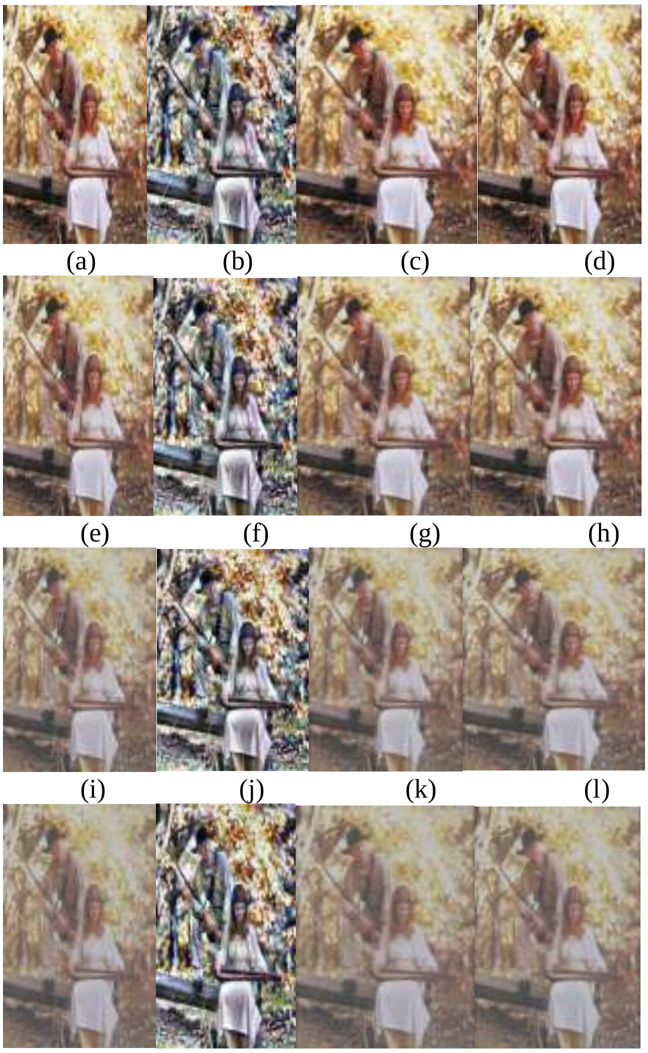
Fig 2: Contrast enhancement of family image with different level of contrast enhancement: Level 1 (row1);Level 2 (row2); Level 3 (row3); Level 4 (row4); Column1 (Low contrast input); Column2 (GHE outputs); Column 3(SECE output): Column 4(SECEDCT output)

TABLE I
EMEG AND GMSD VALUES OF IMAGES RESULTED FROM DIFFERENT ALGORITHMS APPLIED TO FAMILY IMAGE BY DECREASING LEVEL OF CONTRAST FROM LEVEL1 TO LEVEL4 SHOWN IN FIG. 2

TYPE OF ALGORITHM	LEVEL 1		LEVEL 2		LEVEL 3		LEVEL 4	
	EMEG	GMSD	EMEG	GMSD	EMEG	GMSD	EMEG	GMSD
GHE	0.3303	0.2138	O.3282	0.2059	0.3493	0.1925	0.3254	0.1883
SECE	0.1675	0.0389	0.2298	0.0380	0.4724	0.0376	0.3918	0.0394
SECEDCT	0.4698	0.0327	0.4474	0.0320	0.6395	0.0298	0.6049	0.0273

TABLE II
EMEG AND GMSD VALUES OF IMAGES RESULTED FROM DIFFERENT ALGORITHMS APPLIED TO COUPLE IMAGE BY DECREASING LEVEL OF CONTRAST FROM LEVEL1 TO LEVEL4 SHOWN IN FIG. 3

Type of algorithm	Level 1		Level 2		Level 3		Level 4	
	EMEG	GMSD	EMEG	GMSD	EMEG	GMSD	EMEG	GMSD
GHE	0.3117	0.1878	0.3108	0.1964	0.3084	0.1998	0.3078	0.1982
SECE	0.4507	0.0336	0.4318	0.0340	0.3967	0.0356	0.3840	0.0362
SECEDCT	0.5674	0.0270	0.5496	0.0283	0.5149	0.0299	0.5022	0.0361



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k) (l)
(m) (n) (o) (p)

Fig 3: Contrast enhancement of family image with different level of contrast enhancement: Level 1 (row1);Level 2 (row2); Level 3 (row3); Level 4 (row4); Column1 (Low contrast input); Column2 (GHE outputs); Column 3(SECE output): Column 4(SECEDCT output)

V. CONCLUSION

In this paper we proposed efficient SECEDCT (Spatial entropy based contrast enhancement in DCT) algorithm to achieve both global and local contrast enhancement at the same time without visual distortion. SECEDCT extends SECE to perform both global and local contrast enhancement. SECE preserves the shape of the input image's gray-level histogram while improving the contrast. SECEDCT automatically updates transform domain coefficients of an image enhanced by SECE. It can be applied to both color and gray scale images. It statistically shown it can improve contrast of an image meanwhile produce almost no visual distortion on output images. The metrics Expected measure of entropy by gradient (EMEG) and Gradient magnitude similarity deviation (GMSD) of SECEDCT algorithm shows better results compared with GHE, SECE algorithms. The output image enhanced by SECEDCT algorithm is better than the output images of SECE and GHE algorithms.

REFERENCES

[1] T. Celik, "Two-dimensional histogram equalization and contrast enhancement," Pattern Recognit., vol. 45, no. 10, pp. 3810–3824, 2012.

[2] R. C. Gonzalez and R. E. Woods, Digital Image Processing, 3rd ed.Upper Saddle River, NJ, USA: Prentice-Hall, 2006.

[3] D. J. Jobson, Z.-U. Rahman, and G. A. Woodell, "A multiscale retinex for bridging the gap between color images and the human observation of scenes," IEEE Trans. Image Process., vol. 6, no. 7, pp. 965–976,Jul. 1997.

[4] B. Silver, S. Agaian, and K. Panetta, “Logarithmic transform coefficient histogram matching with spatial equalization,” Proc. SPIE, vol. 5817, pp. 237–249, May 2005.
[5] B. Silver, S. Agaian, and K. Panetta, “Logarithmic transform coefficient histogram matching with spatial equalization,” Proc. SPIE, vol. 5817, pp. 237–249, May 2005.
[6] S. S. Agaian, B. Silver, and K. A. Panetta, “Transform coefficient histogram-based image enhancement algorithms using contrast entropy,” IEEE Trans. Image Process., vol. 16, no. 3,
[7] J. Mukherjee and S. K. Mitra, “Enhancement of color images by scaling the DCT coefficients,” IEEE Trans. Image Process., vol. 17, no. 10, pp. 1783–1794, Oct. 2008.
[8] R. Fattal, “Edge-avoiding wavelets and their applications,” ACM Trans.Graph., vol. 28, no. 3, pp. 1–10, 2009.
[9] Q. Wang and R. K.Ward, “Fast image/video contrast enhancement based on weighted thresholded histogram equalization,” IEEE Trans. Consum. Electron., vol. 53, no. 2, pp. 757–764, May 2007.
[10] W. Xue, L. Zhang, X. Mou, and A. C. Bovik, “Gradient magnitude similarity deviation: A highly efficient perceptual image quality index,” IEEE Trans. Image Process., vol. 23, no. 2, pp. 684–695, Feb. 2014.
[11] P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik, “Contour detection and hierarchical image segmentation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 3, no. 5, pp. 898–916, May 2011.

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