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Image Enhancement in Spatial Domain: A Comprehensive Study

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***Abstract*—With the advancement of imaging science, image enhancement has become an important aspect of image processing domain. It is necessary to gather a comprehensive knowledge regarding the existing enhancement technologies to identify and solve their problems and thus to elevate the current image enhancement methodologies. This paper provides the underlying concept of contrast enhancement, brightness preservation as well as brightness enhancement techniques. Besides this, we provide a short description of the existing renowned enhancement methods with their mathematical description and application area. Moreover, experimental results are provided to make a comparative analysis where both qualitative and quantitative measurements are performed. Different enhancement methods are run on same images to examine the qualitative performance. Peak signal to noise ratio (PSNR), normalized cross-correlation (NCC), execution time (ET) and discrete entropy (DE) are quantitative measurement metrics used for quantitative assessment. Most of the cases, it is found that Histogram Equalization has the highest degree of deviation from the input image which basically generates more visual artifacts. Contextual and Variational Contrast enhancement technique takes long time for execution with respect to other enhancement techniques. From our quantitative and qualitative evaluation, we find that Layered Difference Representation performs comparatively produces better enhancement result in all aspect than other existing methods.**

I. Introduction

Nowadays, camera has become inexpensive and thus general people capture large amount of images in their everyday life. In many cases, these images might demand enhancement to make it acceptable to them. The unacceptability of an image might be caused due to various reasons such as lack of operator expertise, quality of image capturing devices, presence of the cloud and the variation of illumination. To enhance the quality of an image for better human visual perception various contrast enhancement techniques have been already proposed [1], [2]. The motivation behind the contrast enhancement is to extract the hidden characteristics of an image. Both contrast and brightness enhancement or brightness preservation plays significant role in image enhancement area. Image enhancement is widely used in atmospheric sciences, astrophotography, medical image processing, satellite image analysis, texture synthesis, remote sensing, digital photography, surveillance and video processing applications. In general, contrast enhancement is performed first for most of the image enhancement methods. Besides this, several other things, such as illumination correction, dark image, and hazy image enhancement are also performed. For image enhancement, these tasks can be performed in different ways such as: spatial domain methods and frequency domain methods. In spatial domain techniques, direct transformation of an image pixel is performed to achieve the intended enhancement. Spatial domain techniques can be categorized into three groups: (a) Global approach (considering the whole image information, a single transformation function is used), (b) Local approach (neighboring pixel information is used to transform each pixel) and (c) Hybrid approach (combination of global and local image enhancement techniques).

Histogram Equalization [1], Exact Histogram Specification [3], Brightness Preserving Bi-Histogram Equalization [4], Recursively Separated and Weighted Histogram Equalization (RSWHE) [5] are the examples of spatial domain methods and Nonsubsampled Contourlet Transform (NSCT) [6], Image Enhancement by Nonlinear Extrapolation in Frequency Space (NEFS) [7] are the examples of frequency domain methods. Time complexity of local image enhancement techniques is high comparing to the global image enhancement techniques. In case of local enhancement, we have to compute the neighboring pixels information for each pixel of an image which increases the time complexity. Fig. 1 illustrates the classification of image enhancement techniques with few illustrative example methods. In this paper, different kinds of spatial domain image

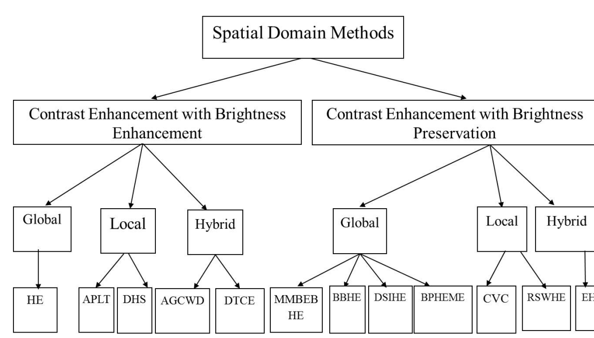


Fig. 1: Classification of Image enhancement techniques

enhancement techniques are described in section II with their implementation and mathematical understanding. Besides this, section III describes a comparative analysis among several image enhancement techniques using different performance evaluation metrics such as Peak Signal to Noise Ratio (PSNR), Normalized cross-correlation (NCC), Execution Time (ET) and Discrete Entropy (DE).

II. IMAGE ENHANCEMENT TECHNIQUES

Histogram equalization (HE) is an important technique and is used in general for image enhancement [1]. To enhance a given image, HE tries to spread the pixels intensity of that image based on the whole image information. As a result, there might be a case where some low intensity pixels are transformed with a high rate and create over-enhancement which is shown in Fig. 2.

Histogram equalization (HE) might also result in mean shift where mean brightness of an input image changes and thus might create undesirable artifacts [4]. Furthermore, due to mean-shift HE is hardly used in consumer electronics products. An improved version of HE is Brightness preserving Bi-Histogram Equalization (BBHE) [4] which tries to overcome mean shift problem. BBHE transforms each pixel by separating the histogram based on the mean values of the image. Therefore, the mean remains fixed and over enhancement problem is reduced. This method firstly separates the histogram of an input image based on the mean brightness and then histogram equalization is applied on each part of the divided histogram. BBHE works well where the input image has symmetric distribution around its mean. However, it might fail for non-symmetric distribution which is shown in Fig. 3.

A similar algorithm of BBHE is Dualistic Sub-Image Histogram Equalization (DSIHE) [8] where histogram separation is done based on median instead of mean. Though DSIHE does not allow significant mean shift in the output image, it also fails to preserve mean brightness in some cases. Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) is an improved version of BBHE and DSIHE to preserve the mean brightness [9] of the image. In MMBEBHE, histogram is separated according to the threshold level, where threshold level is calculated based on the absolute mean brightness error (AMBE). After separating the histogram based on AMBE, histogram equalization is applied on each of the divided part. Though this method enhances the contrast of an image suitably, sometimes it produces more annoying side effects [10].

A combination of BBHE and DSIHE is Recursively Separated and Weighted Histogram Equalization(RSWHE) [5] which comes for brightness preservation and to enhance the contrast of an image. Furthermore, a weighting histogram function is introduced to get a desirable histogram. The core idea of this algorithm is to break down a histogram into two or more portions and then apply a weighting function (based on a normalized power law function) for modifying the sub-histograms. Finally, it performs histogram equalization on each of the weighted histogram. We can figure out this method by Fig. 4. Histogram weighting module gives more probabilities to infrequent gray levels whereas traditional transformation function does not give more probabilities to the infrequent gray levels. However, some statistical information might lose after the histogram transformation and the desired enhancement may not be achieved [11]. Inspired by the RSWHE method, authors of Adaptive Gamma Correction with Weighting Distribution(AGCWD) [11] use gamma correction and luminance pixels probability distribution to enhance the brightness and preserve the available histogram information. The transformation of the gamma correction (TGC) is defined by Eq. 1.

Fig. 4: Functional procedure of RSWHE

$$T(l) = l_{max} * (\frac{l}{l_{max}})^{\gamma} \quad (1)$$

Where, l_{max} is the maximum intensity, and l represents each pixels intensity of an input image and $T(l)$ denotes each input pixel's transformed intensity. Here, a hybrid histogram modification (HM) method is proposed to combine the traditional gamma correction (TGC) and traditional histogram equalization (THE) methods. Though most of the cases this method enhances the brightness of the input image, it might not give satisfactory results when an input image has lack of bright pixels. Because in this case, the highest possible enhancement will never cross the highest intensity of the input image which can be easily understandable from Eq. 1 and also shown in Fig. 6(h).

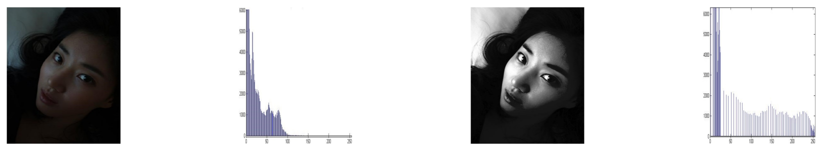
Brightness Preserving Histogram Equalization with Maximum Entropy (BPHEME) [12] preserves image brightness where authors create ideal histogram that maximizes the entropy. They want to preserve the brightness of an image as well as to increase the entropy of the image. Therefore, considering the mean brightness is fixed, BPHEME transforms original histogram to target histogram and then applies histogram specification (HS). As a result, over enhancement effect is reduced. Though this algorithm provides acceptable results for continues case, it fails for discrete ones [12]. Exact histogram specification (EHS) [3] is based on the strict ordering among image pixels. It uses local mean values for enhancement. Here, the histogram and the probability density function (PDF) of the image become uniform after enhancement. Moreover, EHS improves the contrast of an image by maximizing its entropy.

Dynamic Histogram Specification (DHS) [10] preserves the shape of the input image histogram. Along with this, the method also increases the contrast effectively. DHS extracts local maxima using first and second derivatives. Moreover, these two are used to find the critical points (CP). Then direct current is calculated which is combined with the CP to find the specified histogram cumulative density function (CDF) and finally maps the input to the output. Though this algorithm preserves input image characteristics, images are not enhanced significantly.

In Conventional Piecewise Linear Transformation, there are few parameters which should be set manually. Furthermore, such setting may not work effectively for real life images. To mitigate these drawbacks Tsai *et al.* [13] proposed an automatic and parameter free Piecewise Linear Transformation (APLT) function for color images. Their major contribution is to generate automatic and parameter free piecewise linear

(a) **(b)** **(c)** **(d)**

Fig. 2: Test images for dark ocean (a) Original image, (b) Original image histogram, (c) HE , (d) HE histogram



(a) **(b)** **(c)** **(d)**

Fig. 3: Test images for girl (a) Original image, (b) Original image histogram, (c) BBHE, (d) BBHE histogram

transformation function. The locations of the luminance distribution valleys are used to set the input parameters and this distribution is also used to find the number of line segments. The output parameters are set by Eq. 2.

$$O_i = \sum_{n=x}^{c_i} p_r(n) * 255 \tag{2}$$

Here, O_i represents output parameters, $p_r(n)$ represents luminance probabilities of the distribution, x is the starting luminance of the histogram.

In general most of the contrast enhancement methods fail to produce satisfactory results for color images such as dark, low-contrasted, bright, mostly dark, high-contrasted, and mostly bright images [14] . Thus, Tsai *et al.* [14] proposed a decision tree-based contrast enhancement algorithm, which is used to decide the type of input image whether it is dark, low-contrasted, bright, mostly dark, high-contrasted or mostly bright. After deciding the input image type, piecewise linear transformation is applied to enhance the image. This method performs well for skin detection, visual perception and image subtraction measurements [14].

Celik and Tjahjadi proposes Contextual and Variational Contrast enhancement (CVC) [15] which is effective to create better visual quality output image. The contrast is increased here by using inter pixel contextual information. The mutual information of each pixel and its neighboring pixels are used to create a 2D histogram and the enhancement is performed by using a smoothed version of this histogram. For this, they map the diagonal elements of the input histogram to the diagonal elements of the target histogram. This algorithm produces comparatively better enhanced image as compared to other existing methods which is shown in Fig. (5- 9). But the computational complexity of this method is high and become higher with the increment of differences among neighboring pixels.

Global enhancement methods cannot always provide satisfactory results. For example, when there is a sudden peak in the input histogram, global enhancement methods does not work well. Layered Difference Representation (LDR) [16] comes to overcome this problem. The authors claim that better enhancement can be achieved by using four neighbors. They first classify different gray levels into multiple layers, which are similar to a tree structure for deriving a transformation function. The transformation function can be determined by Eq. 3. Here, ${d_i}^1$ is the difference of the intensities at layer 1 of the tree and x_k represents the summation of all difference occurred in layer 1.

$$x_k = \sum_{i=0}^{k-1} {d_i}^1 \tag{3}$$

After getting the transformation functions for each layer, all of those are aggregated to achieve the desired transformation function. Though LDR works with sudden peaks, it cannot perform accurately. Sudden peaks are more accurately handled using histogram modication framework (HMF) [17]. HMF depends on histogram equalization and contrast enhancement of an image. Besides, this method can handle noise and spikes of an image using black and white stretching with an optimization procedure. Different levels of contrast enhancement are used here along with several adaptive parameters. However, these parameters have to be manually tuned to achieve high level of contrast.

III. Experimental Results

This section summarizes the experimental results produced by HE [1], EHS [3], HMF [17], LDR [16], CVC [15], RSWHE [5] and AGCWD [11]. To enhance the contrast as well as to preserve or enhance the brightness of an image, these methods are applied on various grayscale and color images. In this paper, we separate our experimental results into two sections: (a) qualitative measurement and (b) quantitative assessment. For qualitative measurement, we consider only visual assessment and for quantitative analysis we consider Peak Signal to Noise Ratio (PSNR), Normalized Cross-Correlation (NCC), Execution Time (ET) and Discrete Entropy (DE). We use MATLAB 2012 for getting experimental result of the image.

A. Visual Assessment

In this section, image enhancement of each method is measured by visual assessment. Though a large number of images are used for testing purpose, we show the results using

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only five images due to page limitations. Among five test images, we consider three color and two grayscale images named *building*, *woman*, *girl*, *bean* and *cameraman* respectively.

We see HE (b) of Fig. (5-9) directly tries to equalize the original image histogram and loses some intensity information. Though some artifacts exist, output image can be clearly visualized because of the brightness increment. EHS performs a strict ordering among image pixels and histogram guarantees to maintain uniformity among the pixels. As a result, brightness and contrast are increased. Using black and white stretching HMF (d) of Fig. (5-9) tries to mitigate the noise of an image such as sudden spikes. LDR separates image into several layers based on intensity results to preserve the brightness is shown in figure (e) of Fig. (5-9). The RSWHE (g) of Fig. (5-9), makes some artifacts due to increase in the probability of infrequent pixels. AGCWD enhances the brightness of an image like (h) of Fig. (5-9). In Fig. 6(a), the original bean image has no too bright pixels and according to our statement, it cannot enhance the contrast or brightness of an image. As a result, output image is as equal as input image which is shown in Fig. 6(h).

B. Quantitative Evaluation

Enhancement or improvement of the visual quality of an image is a subjective matter because it could vary from person to person. Through quantitative measurements, we want to establish a mathematical proof of whether the quality of an image is enhanced or not. Though quantitative evaluation of image enhancement is not an easy task due to the acceptable criterion, we assess the performance of enhancement techniques using four quality metrics such as PSNR, NCC, ET and DE.

1) Peak Signal-To-Noise Ratio: Most of the cases the more the PSNR, the better visual quality of the image has. Table I represents discrete statistical data of PSNR for each image after applying enhancement techniques and Fig. 10(a) presents a graphical correlation among different methods with respect to PSNR. From the statistical result, we can conclude that LDR has the highest PSNR in most of the cases. So, in this case the performance of LDR is best.

TABLE I: PSNR (Peak Signal-To-Noise Ratio)

Image Name	HE	EHS	HMF	LDR	RSWHE	AGCWD	CVC
Cameraman	19.1	19.22	26.68	33.22	14.65	18.25	24.65
Bean	11.76	11.85	19.13	12.69	27.25	35.91	15.80
Girl	6.91	6.94	18.40	12.85	16.22	20.72	11.04
Building	9.10	9.11	19.30	23.61	16. 23	16.49	20.30
Woman	8.74	8.76	16.91	22.64	13.83	16.07	12.86

2) Normalized Cross-Correlation: Normalized cross-correlation is used for measuring the difference between input and output image. Table II and Fig. 10(b) represent NCC of several images using multiple enhancement techniques. From the Table II and Fig. 10(b), we can conclude that high difference exists in HE and EHS means that the rate of enhancement or changing is high in HE and EHS. As a result, HE produces high rate of artifacts which is also proved by qualitative assessment of the image.

TABLE II: NCC (Normalized Cross-Correlation)

Image Name	HE	EHS	HMF	LDR	RSWHE	AGCWD	CVC
Cameraman	1.09	1.08	1.06	0.96	1.35	1.17	0.89
Bean	1.23	1.23	1.02	1.00	1.10	1.03	1.15
Girl	3.90	3.89	1.85	2.63	2.08	1.64	3.00
Building	1.09	1.08	1.04	1.00	1.09	0.73	1.01
Woman	2.13	2.12	1.44	1.25	1.64	1.49	1.73

3) Execution time: The execution time is an essential metric in image processing due to have a strong correlation between time and quality. So, a tradeoff needs to determine between those. Table III presents execution time needed to run each algorithm. We plot execution time into graph at obtain Fig. 10(d). From Table III and Fig. 10(d) it is clear that CVC takes more execution time. On other hand, most of the cases EHS needs lowest execution time. In this sense, EHS is the best technique among the described image enhancement methods.

TABLE III: Execution time (second) of each algorithms

Image Name	HE	EHS	HMF	LDR	RSWHE	AGCWD	CVC
Cameraman	0.07	0.04	0.14	0.10	0.36	0.22	0.16
Bean	0.24	0.10	0.46	1.24	0.55	0.27	22.25
Girl	0.22	0.12	0.36	0.78	0.66	0.23	17.06
Building	0.39	0.15	0.87	2.32	1.30	0.25	41.65
Woman	0.58	0.27	0.97	2.48	2.03	0.33	55.03

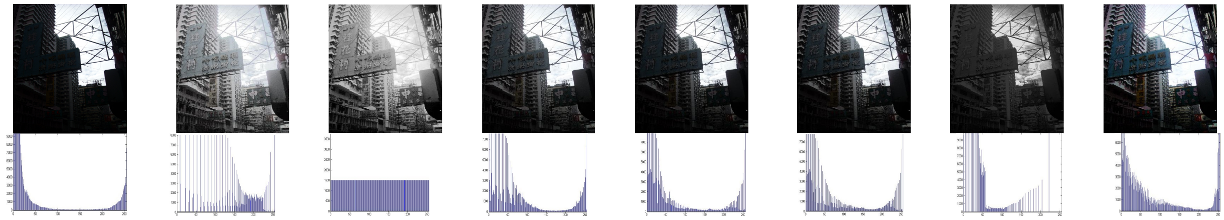
4) Discrete Entropy: Entropy is a measurement of uncertainty of a random variable. The more the variable is random, the more entropy an image has [18]. In image processing, low entropy means image has low contrast. Table IV and Fig. 10(c) illustrates the discrete entropy for each algorithm and it proves that most of the cases EHS holds large entropy. So, in this case EHS also performs better than other if we give importance on the contrast of enhanced image.

TABLE IV: Discrete entropy of each algorithms

Image Name	HE	EHS	HMF	LDR	RSWHE	AGCWD	CVC
Cameraman	6.77	8.00	6.96	6.91	6.89	7.01	6.81
Bean	5.06	8.00	5.10	5.11	4.78	5.11	5.07
Girl	6.85	8.00	6.55	6.88	6.62	5.84	6.96
Building	7.30	8.00	6.95	6.71	6.82	6.03	6.88
Woman	7.77	8.00	7.40	7.17	7.56	6.77	7.60

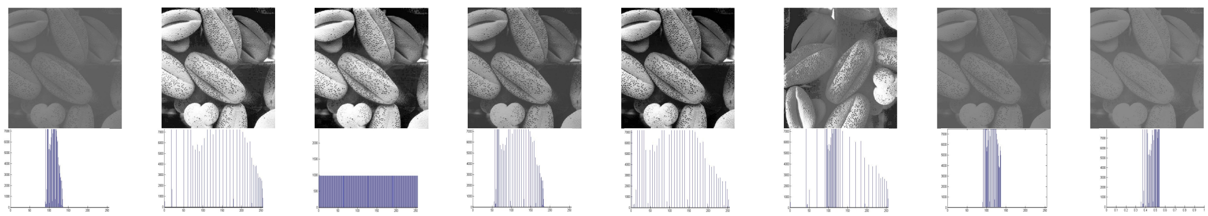
IV. Conclusion

In this survey paper, we provide a short description of several techniques and algorithms used for image enhancement. Moreover, a comparative study of image enhancement techniques, their advantages, limitations and application areas are presented here. The performance of image enhancement techniques is assessed by several evaluation metrics. Using PSNR metric we can conclude that LDR performs best. In Cross-Correlation, most of the cases HE have the highest level of enhancement that means HE has the maximum rate of deviation between the original and the enhanced image. CVC takes too long execution time than other enhancement techniques and finally in accordance with discrete entropy EHS has the highest value.



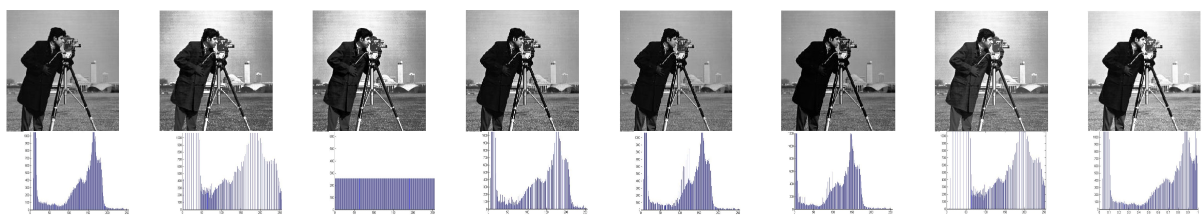
(a) Original **(b)** HE **(c)** EHS **(d)** HMF **(e)** LDR **(f)** CVC **(g)** RSWHE **(h)** AGCWD

Fig. 5: Test image for *"building"* and their corresponding histogram



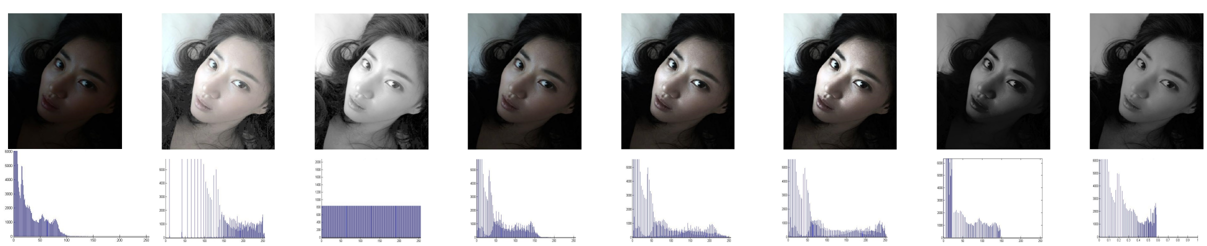
(a) Original **(b)** HE **(c)** EHS **(d)** HMF **(e)** LDR **(f)** CVC **(g)** RSWHE **(h)** AGCWD

Fig. 6: Test image for *"bean"* and their corresponding histogram



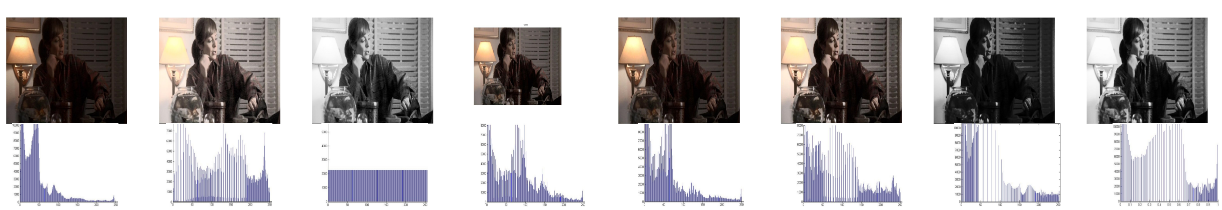
(a) Original **(b)** HE **(c)** EHS **(d)** HMF **(e)** LDR **(f)** CVC **(g)** RSWHE **(h)** AGCWD

Fig. 7: Test image for *"cameraman"* and their corresponding histogram



(a) Original **(b)** HE **(c)** EHS **(d)** HMF **(e)** LDR **(f)** CVC **(g)** RSWHE **(h)** AGCWD

Fig. 8: Test image for *"girl"* and their corresponding histogram

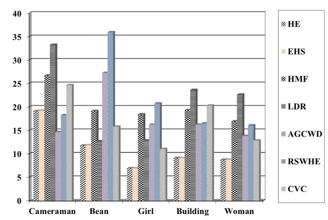


(a) Original **(b)** HE **(c)** EHS **(d)** HMF **(e)** LDR **(f)** CVC **(g)** RSWHE **(h)** AGCWD

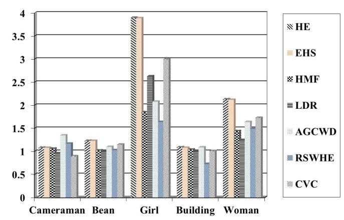
Fig. 9: Test image for *"woman"* and their corresponding histogram

TABLE V: Comparison of Contrast Enhancement Techniques

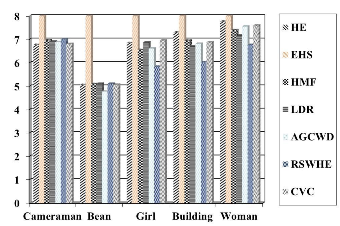
Method Name	Advantages	Limitation	Application
HE [1]	Enhances contrast.	Brightness preservation is not possible.	Medical image processing, radar signal processing, texture synthesis and speech recognition.
BBHE [4]	Overcomes mean shift problem for symmetric distribution.	Synthetic enhancement occurs as well as fails to preserve brightness for non-symmetric distribution.	Consumer electronics such as TV, VTR, camcorder.
DSIHE [8]	Preserves mean brightness in some cases.	Fails when the density of an image is very high with narrow range.	Consumer electronics products.
MMBEBHE [9]	Preserves maximum brightness in some cases.	Creates more annoying side effects and high computation time is needed.	Consumer electronics such as TV, camcorder.
EHS [3]	Gives maximum information of the image, provides good visual quality.	Cannot give any obvious choice for the desired histogram.	Image watermarking.
RSWHE [5]	Preserves brightness, gives more probabilities to infrequent gray levels.	Lose some statistical information, consumes more time due to recursion.	Medical images.
AGCWD [11]	Brightness enhancement, low computation cost.	Cannot give satisfactory result when image has no bright pixel or high intensity pixel.	Works for dimmed images, videos.
DHS [10]	Preserves input image histogram shape.	Images are not enhanced significantly.	Electric devices such as mobile phone, digital camera, mobile handset and small LCD panel.
CVC [15]	Generates visually pleasing image, preserves the content of an image.	Computational complexity is large.	Applied on both grey-level color images, face recognition.
LDR [16]	Better image enhancement performs.	Cannot handle sudden peaks more accurately.	Mainly in consumer electronics products.
HMF [17]	Sudden peaks are more accurately handled.	Parameters are manually tuned.	Video image processing.



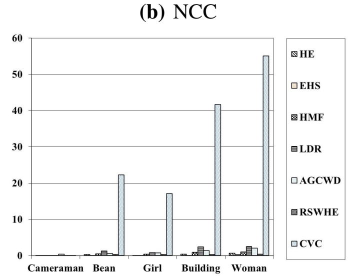
(a) PSNR



(b) NCC



(c) DE



(d) ET

Fig. 10: Comparison of different techniques using (a) PSNR,(b) NCC, (c) DE, (d) ET

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