CONTRAST ENHANCEMENT BY USING HISTOGRAM-BASED TECHNIQUES

A PROJECT REPORT

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BONAFIDE CERTIFICATE

This to certify that this project work titled **CONTRAST ENHANCEMENT BY USING HISTOGRAM-BASED TECHNIQUES** is the bonafide work of **Vadlamudi Bhanu Prakash(Y19IT118)**, **Mohammed Tahir Mohiuddin (Y19IT074)**, **Sayana Mouni (L20IT137)** who have carried out the work under my supervision and submitted in partial fulfilment of the requirement for the award of the degree, **BACHELOR OF TECHNOLOGY**, during the year 2022-2023.

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ABSTRACT

The development of contrast enhancement (CE) techniques has been an important and essential issue in image processing fields. Histogram equalization (HE) is the mostly used technique for CE. It makes the output histogram approximate a uniform distribution by spreading out the dynamic range of the gray intensity values. Various histogram-based CE methods have been suggested to overcome the drawbacks. This project aims to develop a novel global CE model by using 1D histogram-based techniques to enhance the entire contrast. The proposed algorithm uses the locality condition to form a global CE with the locality-preserving property, meaning that the local structure of the histogram is preserved after histogram processing. The algorithm is tested against different images using subjective and objective analysis. Compared with several enhancement algorithms, the proposed algorithm shows highly competitive.

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List of Abbreviations

CE	**-**	Contrast Enhancement
HE	**-**	Histogram Equalization
CLAHE	-	Contrast Limited Adaptive Histogram
SPOHE	**-**	Stratified parametric oriented histogram equalization
BHEP	**-**	Bilateral Histogram Equalization with Pre-Processing
RMS	**-**	Root Mean Square
GHE	**-**	Global Histogram Equalization
LHE	**-**	Local Histogram Equalization

Chapter 1

Introduction

Image enhancement methods referred to a collection of different techniques that search for the improvement of the photographic appearance of an image or for converting the image to a form which is better suitable for the analysis of a machine or a human. In many applications and research areas the enhancement of noisy image data is a big technical problem. Image enhancement approaches can be grouped into three extensive categories such as Frequency domain methods, which are based on the Fourier transformation of an image, spatial domain techniques, which are based on the pixels directly, and Fuzzy domain techniques, which comprises the use of knowledge-based systems that are able to imitate the activities of a human expert. The main advantages of spatial based domain techniques are the low complexity which brings the favours in real time implementations and they are conceptually simple to understand. However, these methods commonly lacks in providing imperceptibility and adequate robustness requirements. In these we are using the contrast enhancement techniques that are based on the 1D and 2D histogram. In general 2D histogram is used for density heatmap, whereas 1D histogram is used for histogram equalization.

1.1. Applications Of Contrast Enhancement

Contrast enhancement is a significant factor in any subjective evaluation of image quality which used to enhance the overall quality of the medical image for feature visualization and clinical measurement. This study presents a number of contrast enhancement techniques for medical images analysis. These techniques were applied on different type of medical images such as: MRI, CT-Scan and X-ray to improve image quality and come up with an acceptable image contrast.

Image enhancement plays a fundamental role in a variety of applications enhancement is the manner of improving the certain attribute of image and reducing the noise recently much work has already been proposed till now for enhancing the digital images. This paper has presented a relative comparison of a mixture of image enhancement techniques and mostly focused on histogram and fuzzy logic techniques.

Contrast is an important factor in any subjective evaluation of image quality. Contrast is created by the difference in luminance reflected from two adjacent surfaces. In other words, contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception, contrast is determined by the difference in the colour and brightness of the object with other objects. Our visual system is more sensitive to contrast than absolute luminance therefore, we can perceive the world similarly regardless of the considerable changes in illumination conditions. Many algorithms for accomplishing contrast enhancement have been developed and applied to problems in image processing.

Contrast enhancement techniques have various application fields especially in medical imaging for enhancing the visual quality of low contrast images. It is a required step in medical image analysis for highlighting important features that are not properly visible.

Contrast enhancement amplifies the visual difference adjacent structures in images and can reveal more information about organs or tumors shown in image and sharpen the edges between them.

There are many techniques for enriching image contrast such as neighbourhood operation, average filter, bilateral ratinex, imadjust and sigmoid function. These techniques are compared with each other to achieve which enhancement technique produces a better contrast of an image.

1.2. Literature Survey

Mithilesh Kumar and Ashima Rana, they present a hybrid technique which is composed of three methods. They have present the Image Enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE) method and Wiener filter to eliminate the noise which can be present in the digital image. They also used Gamma correction technique into transfer the image into acceptable dynamic range. To avoid amplifying any noise that might be present in an image they have used contrast limited adaptive histogram equalization parameter to bound the contrast especially in homogeneous area. As a conclusion they get the following results. The Contrast Limited Adaptive Histogram Equalization technique and Wiener filtering yields perfect contrast enhancement while preserving the brightness of given image and suitable for images enhancement. Wiener filter is good for image sharpening and Limited Adaptive Histogram Equalization method is better for contrast enhancement of the image.

Y. F. Liu; J. M. Guo proposed a contrast enhancement technique, known as stratified parametric oriented histogram equalization (SPOHE) is proposed to provide a regional enhanced effect without visual artifacts, e.g., blocking artifacts, which normally incurred in the former simplified enhancement technique. The stratified sampling theory is applied to uniformly distributed samples the original image through many divided strata with size defined by the two parameters (,). Moreover, the required statistical information are efficiently derived through the integral image concept. Eventually, the corrected SPOHE (CSPOHE) is also proposed to further improve the contrast with a limited trade off computation. Experimental results demonstrate that the proposed technique produces a similar CDF to the original one for an accurate contrast enhancement performance while significantly decreases the computational complexity. Moreover, comparing with the old speed oriented technique good contrast and error-free results can be produced simultaneously.

Jan et al. stated that in order to achieve a good stability between power consumption and visual perception, authors have suggested a histogram-based power saving algorithm to enhance the image contrast for OLED display panels. The suggested algorithm amends the empty bins of the image histogram graph as a pre-process of power depletion. Additionally, the visual effect was reimbursed using the power saving histogram equalization algorithm. Experimental results show that the suggested algorithm not only reduces the display power, but also generates the highly perceptual contrast of the digital images. They have suggested the PSHA (Power Saving Histogram Algorithm) algorithm to be the pre-processing of the image enhancement algorithms for OLED panels. They have presented the embodiment that modified the PCCE algorithm to adaptively generate the parameter according to the image characteristic. Compared to the prior work, the proposed PSHA (Power Saving Histogram Algorithm) algorithm effectively balances the effect between contrast enhancement and power reduction. In our future works, the statistical data of the transformation curve will be analysed to construct Look Up Table for the real-time hardware implementation. Moreover, the approach mentioned in this paper is only applied to static images. One of the future directions would be investigating extended methods that are applied to video sequences.

P. Gupta and A. Dhingra stated that the alteration model of a histogram which is elementary to take care of such sort of issues as per trait of implementation. The bounded estimations which are two in number of backing of histogram chart are invented and positioned to relating qualities, individually. The probability density function for calculating probability of the digital image is then is enumerate & revised function of mapping is utilized to achieved HE. Outputs of trial demonstrate that the methodology suggested may viably enhance image standard revamp by HE & HM routines, & even HR called as redistribution of histogram, for example, (GLG) grouping of gray level, RGB colour spacing and colour maintaining methods. Taking R, G and B component individually and remap them. In most prevailing methods of CE, refer to the enhancement of Contrast don't take into consideration of issues with a substantial extent of section of gray is retained in the periphery of backing of chart of the histogram. In particular document, we suggest a modified scheme of an elementary chart of histogram to manage this concern. The mentioned plan can be connected in HR, HS and HE methods along with colour images. Test results exhibit that our proposed plan can viably and essentially dispose of the stonewashed impression & nasty artifacts incited because of few current methodologies. Moreover, it may be anticipated that the computed picturisation of the image is making use of the tricks that are suggested, that takes into the account of some issues ingrained in a section of histogram chart, may retain their original glimpse.

S. Zhang, J. Pang, H. Chen and S. Zhang authors have suggested a new spatially different operator based on the layered iCAM06 model and image enhanced adaptive histogram equalization. They have first disintegrated the HDR image into base layer and detail layer, and then apply the image enhanced operator to all layers.

Last, they experiment the operator on a series of HDR luminance image, and get adequate result with enhanced contrast and visual sensation, as well as lowered time cost with respect the original iCAM06 operator. The developed operators revamp the contrast and details, as well as the visual sensation of all the LDR images comparing to the native operator. In this paper, we propose a new tone mapping operator to tone-map HDR image. We apply a layered model and CEAHE to tone map the HDR image and get satisfactory result. The experiment of our operator and iCAM06 model shows that, our operator lowers the time cost of layering of HDR image by a fast algorithm of bilateral filter, and also improves final contrast and detail of the LDR image by CEAHE. In the future, the operator can be further improved with respect to the HVS theory to give better image sensation, and faster algorithm and more vivid LDR image can be rendered by the operator. And our future work will also cope with the implementation of adaptive operator with automated fitted parameters. Totally, faster and more improved tone-mapping algorithm can be obtained with our newly proposed tone-mapping knowledge.

S. P. Panda author is suggested a brand new technique of interpolation by using fuzzy logic interpolation. The suggested technique is used to define pixel intensity level transformation function form a group of locally stretched pixel intensity. The transformation function obtained from proposed method is applied to coloured image and then compared with the results produced from cubic spline interpolation method. The comparison results illustrates that the suggested technique can be used for interpolation to enhance contrast of an image. The methods described in the previous sections are implemented using MATLAB® R2013 software. The Fuzzy Logic Toolbox provided in the MATLAB software is used to evaluate the data and was stored in a look-up-table. The interpolation results stored in a look-up-table for locally stretched image points are applied to the image. As the image is a coloured image in RGB format, the image format is converted to HSV format and then the intensity interpolation information form look-up-table is applied to the converted image. The images are contrast enhanced images due to cubic spline interpolation and fuzzy based interpolation respectively. The pixel intensity transformation curve of fuzzy based interpolation and cubic spline interpolation. The Root Mean Square (RMS) contrast of the actual image, cubic spline based contrast enhanced image and fuzzy interpolation based contrast enhanced image. The results obtained from the fuzzy logic based interpolation are very promising and inspiring. The method used in this paper is the simplest of all fuzzy logic methods. There are so many advanced methodology developed due to extensive research in field of fuzzy logic, which may be used to obtain better results for fuzzy based interpolation. This paper concludes that, the fuzzy logic interpolation method can be used for contrast enhancement purposes, although, the transformation curve of fuzzy interpolation deviates slightly. Reduction of this slight deviation using advanced fuzzy methods will be a future scope of research.

Amil et al authors have introduced a new image enhancement technique namely Bilateral Histogram Equalization with Pre-processing (BHEP) which uses Harmonic mean to divide the histogram of the image. They have performed both qualitative and quantitative measurements for experiments and the results show that BHEP creates less artifacts in several standard images than the existing state-of-the-art image enhancement techniques. In this research paper, a new medical image illumination enhancement and sharpening technique based on SWT was proposed. The proposed technique decomposed the input image into four sub bands by employing SWT.

Afterwards the illumination of LL sub band image was being enhanced by combining the input image and the LL sub band image using weighted sum rule. Finally the output was obtained by applying ISWT on updated LL and the high frequency sub bands of original image which was resulting in sharper image. The proposed technique was compared with the GHE, LHE, SVE, and DWT+SVD techniques and the visual result were illustrated in the paper. Qualitative outputs were confirming the superiority of the proposed technique over the conventional and the state-of-art techniques.

1.3. Objective of Work

The goal of contrast enhancement is to increase the contrast, without saturating the pixels (loosing visual information) or causing a significant shift in the image brightness. If the contrast of an image is highly concentrated on a specific range, e.g. an image is very dark; the information may be lost in those areas which are excessively and uniformly concentrated. The problem is to optimize the contrast of an image in order to represent all the information in the input image. It is a very common image processing technique for enhancing features in low contrast images. Several methods like Contrast Stretching, Histogram Equalization, Adaptive Histogram Equalization, Contrast-Limited Adaptive Histogram Equalization or CLAHE, etc. have been used for enhancing the contrast of images

1.4. Scope of Work

Contrast enhancement is a significant factor in any subjective evaluation of image quality which used to enhance the overall quality of the medical image for feature visualization and clinical measurement. This study presents a number of contrast enhancement techniques for medical images analysis. These techniques were applied on different type of medical images such as: MRI, CT-Scan and X-ray to improve image quality and come up with an acceptable image contrast. The proposed method included different enhancement techniques: logarithm and Exponential equations was created to improve the illumination and contrast of medical images, Image quality coefficients were extracted and compared with image quality coefficients for the same images, which were processed by the modified filter, and showed that the proposed method gave better results.

Chapter 2
Existing Methods

2.1. Local Enhancement:

Image enhancement procedures comprise of a gathering of strategies that try to enhance the visual presence of a picture or to change over the picture to a structure more qualified for examination by a machine or a human. The rule goal of picture upgrade improvement strategies is to process a picture so that the outcome is more suitable than the first picture for a particular application.

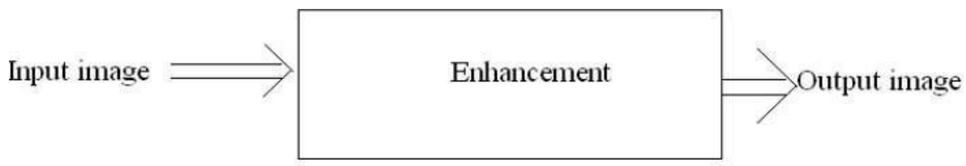


Figure 1**:** Operation of Image Enhancement

It is regularly used to build the complexity in pictures that are considerably dull or light. In Figure(1) upgrading involves operations that enhance the appearance to a human viewer, or operations to change over a picture to an organization more qualified to machine preparing. Picture upgrade alludes to those picture handling operations that enhance the nature of information picture with a specific end goal to beat the shortcoming of the human visual framework.

2.1.1. Introduction:

Image enhancement methods is divided into three broad classes:

2.1.2.1. Spatial Domain methods.

2.1.2.2. Frequency Domain methods

2.1.2.3. Fuzzy Domain

2.1.2.1. Spatial Domain Methods:

Spatial domain methods which work directly on the pixels. Spatial domain system pixel qualities may be changed by that rely on upon the first pixel esteem (neighbourhood or point forms). On the other hand, pixel qualities may be joined with or contrasted with others in their quick neighbourhood in an assortment of ways.

Suppose f(x, y) be a novel image, where x, y are the image co-ordinates and f is the gray level value. For example, 8-bit image, f has the values from 0 – 255. Where black denotes 0, White denotes 255 and all the intermediate values represents glooms of gray.

Here f(x, y) is the original image and T is the transformation applied to it to get a new modified image g(x, y). The worker T is applied at every location (x, y) to yield output g at that place. Spatial domain enhancement can be done in two ways:

1. Point processing
2. Neighbourhood processing

Some of the examples of point processing are digital negative, contrast stretching, Thresholding etc. Some of the examples of neighbourhood processing are image filtering that is max, min, mean, median etc. these are the order statistical filters.

2.1.2.2 Frequency Domain Methods:

Frequency domain works on Fourier transform of an image.

1. Edges and sharp moves e.g., clamour in a picture contribute essentially to high recurrence substance of Fourier change.
2. Low recurrence substance in the Fourier change are capable to the general appearance of the picture over smooth zones.

The idea of separating is simpler to envision in the recurrence space. Thusly improvement of picture f(x, y) should be possible in the recurrence area in view of DFT. This is especially helpful in convolution. in the event that the spatial degree of the point spread grouping h(x, y) is expansive then convolution hypothesis g(x, y) is enhanced image.

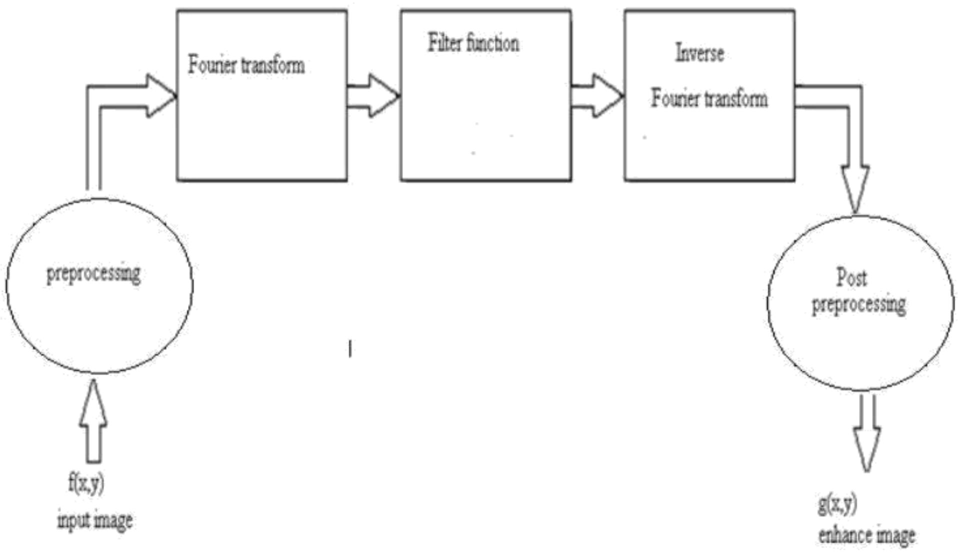


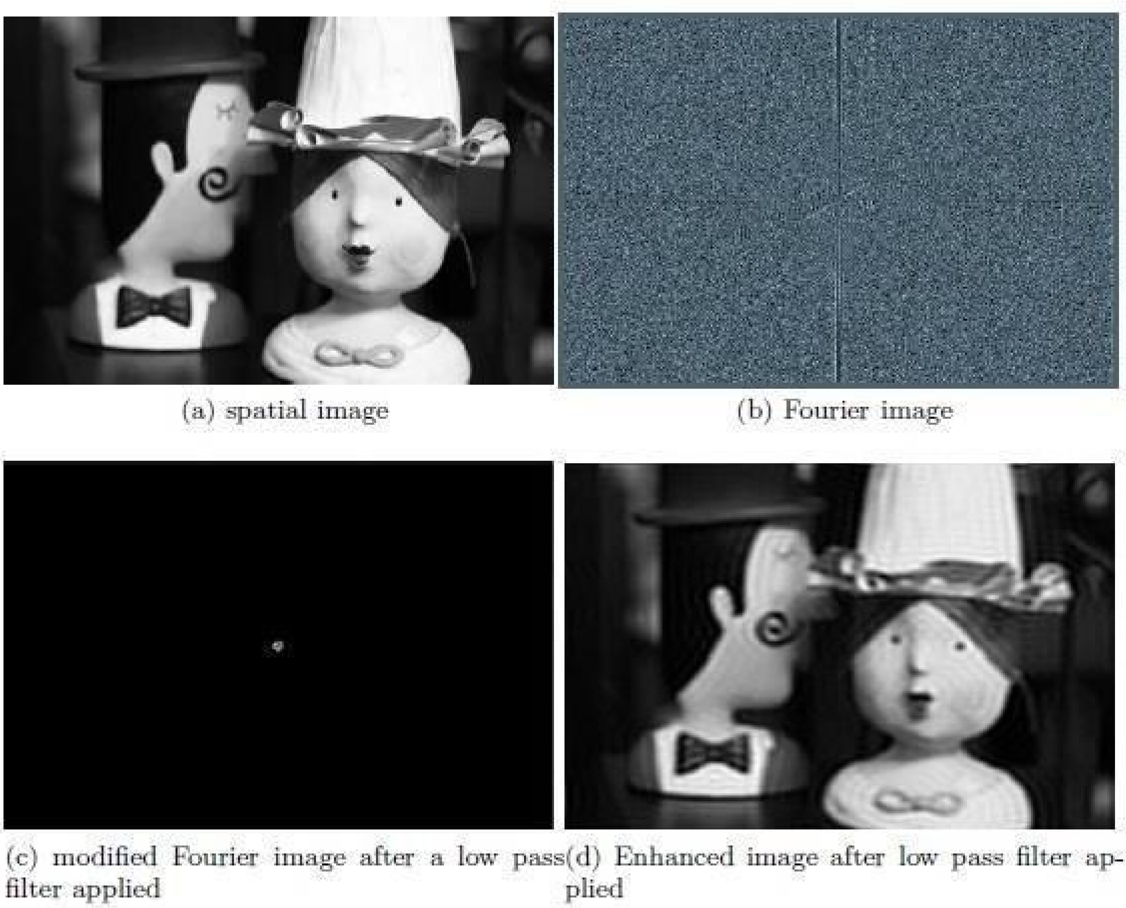
Figure 2**:** Basic steps for Frequency Domain

In the above Figure (2) a digital image is converted from spatial domain to frequency domain. In the frequency domain, image filtering is used for image enhancement for a specific application. A Fast Fourier transformation is a tool of the frequency domain used to convert the spatial domain to the frequency domain

2.1.2.3. Fuzzy Domain:

Fuzzy set hypothesis is therefore valuable in taking care of different vulnerabilities in PC vision and picture preparing applications. Fluffy picture preparing is a gathering of distinctive fluffy ways to deal with picture handling that can comprehend, speak to, and process the picture. It has three principal stages, to be specific picture fuzzification, alteration of participation capacity qualities, and defuzzification. Fluffy picture upgrade is in view of dim level mapping into enrolment capacity. The fact is to make a photo of higher unpredictability than the first picture by giving a greater weight to the dull levels that are closer to the mean faint level of the photo that are more far off from the mean.

2.1.3 Results:

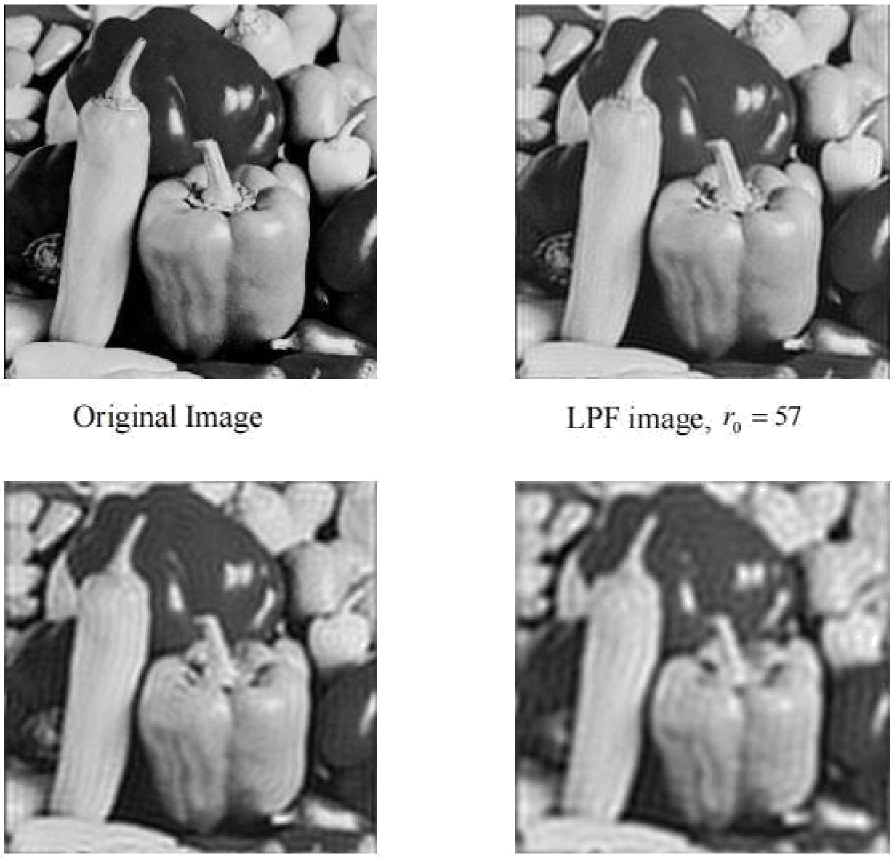


(a) spatial image (b) Fourier image

(c) modified Fourier image after a low pass filter applied (d) Enhanced image after low pass filter applied

Figure:3 Results on different filters

The above figure(3) contains a spatial image, fourier image, modified fourier image after a low pass filter applied and enhanced image after low pass filter applied. We can observe that fourier image is so blur and we cannot see any details in that image. In modified fourier image after a low pass filter where all low frequency components are taken while high frequency components are removed. This image causes no details just a blink spot. We can see a clear image in enhanced image after low pass filter applied.



Original Image

LPF image, $r_0 = 57$

LPF image, $r_0 = 36$

LPF image, $r_0 = 26$

Figure 4: Ideal low pass filter

The above figure(4) Notice the severe ringing effect in the blurred images, which is a characteristic of ideal filters. It is due to the discontinuity in the filter transfer function here cut off frequency r0 of the ideal LPF determines the amount of frequency components passed by the filter. Smaller the value of r0, more the number of image components eliminated by the filter. In general, the value of r0 is chosen such that most components of interest are passed through, while most components not of interest are eliminated.

2.2 Histogram Equalization:

Histogram equalization usually increases the global contrast of many images, especially when the image is represented by a narrow range of intensity values. Through this adjustment, the intensities can be better distributed on the histogram utilizing the full range of intensities evenly. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the highly populated intensity values which are used to degrade image contrast.

It is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are either over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique adaptive to the input image and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

There are two ways to think about and implement histogram equalization, either as image change or as palette change. The operation can be expressed as P(M(I)) where I is the original image, M is histogram equalization mapping operation and P is a palette. If we define a new palette as P'=P(M) and leave image I unchanged then histogram equalization is implemented as palette change or mapping change. On the other hand, if palette P remains unchanged and image is modified to I'=M(I) then the implementation is accomplished by image change. In most cases palette change is better as it preserves the original data.

2.2.2. Methodology

There are two types in Histogram equalization

1.Adaptive histogram equalization

2. Contrastive limited adaptive equalization

Adaptive Histogram Equalization

Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image.

Contrastive Limited Adaptive Equalization

Contrast Limited AHE (CLAHE) differs from adaptive histogram equalization in its contrast limiting. In the case of CLAHE, the contrast limiting procedure is applied to each neighbourhood from which a transformation function is derived. CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to.

Algorithm

Compute the histogram of pixel values of the input image. The histogram places the value of each pixel [,] into one of L uniformly-spaced buckets h[ ] Where =2^8 and the image dimension is ×

- Calculate the cumulative distribution function

- Scale the input image using the cumulative distribution function to produce the output image.

Where CDF min is the smallest non-zero value of the cumulative distribution function

Steps involved

1. Get the input image
2. Generate the histogram for the image
3. Find the local minima of the image
4. Divide the histogram based on the local minima
5. Have the specific gray levels for each partition of the histogram
6. Apply the histogram equalization on each partition

Global histogram equalization (GHE)

GHE is very simple and fast, but its contrast enhancement power is low. Here the histogram of the whole input image is used to compute the histogram transformation function. As a result, the dynamic range of the image histogram is flattened and stretched. The overall contrast is improved.

Local histogram equalization (LHE)

LHE can enhance the overall contrast more effectively.

One of the drawbacks of histogram equalization is that it can change the mean brightness of an image significantly as a consequence of histogram flattening and sometimes this is not a desirable property when preserving the original mean brightness of a given image is necessary. Bi-Histogram Equalization was proposed to overcome this problem.

2.2.3 Results:

Adaptive Histogram Equalization

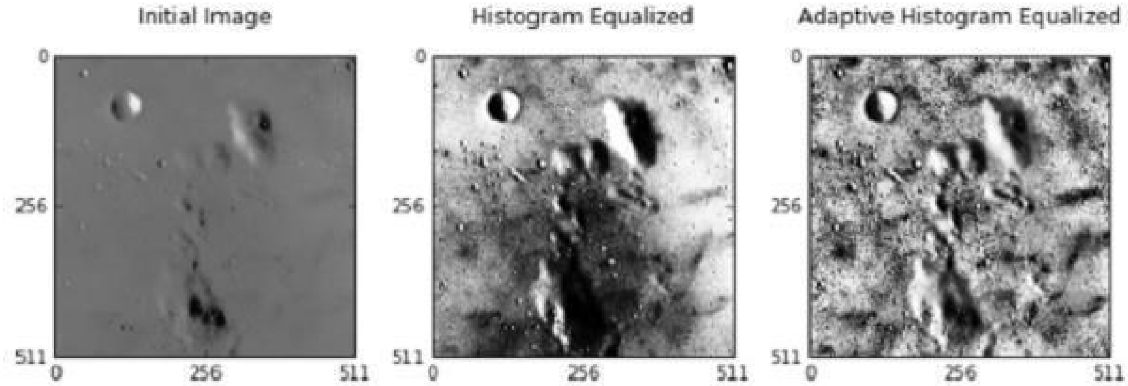


Figure 5: Adaptive Histogram Equalization

In above Figure (5) Adaptive Histogram Equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image

The size of the neighbourhood region is a parameter of the method. It constitutes a characteristic length scale: contrast at smaller scales is enhanced, while contrast at larger scales is reduced Due to the nature of histogram equalization, the result value of a pixel under AHE is proportional to its rank among the pixels in its neighbourhood. This allows an efficient implementation on specialist hardware that can compare the center pixel with all other pixels in the neighbourhood. An unnormalized result value can be computed by adding 2 for each pixel with a smaller value than the center pixel, and adding 1 for each pixel with equal value. When the image region containing a pixel's neighbourhood is fairly homogeneous regarding to intensities, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixel values to the whole range of the result image. This causes AHE to overamplify small amounts of noise in largely homogeneous regions of the image

Figure 6**:** Contrastive Limited Adaptive Equalization

Contrast Limited AHE (CLAHE) figure(6) differs from adaptive histogram equalization in its contrast limiting. In the case of CLAHE, the contrast limiting procedure is applied to each neighborhood from which a transformation function is derived. CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to.

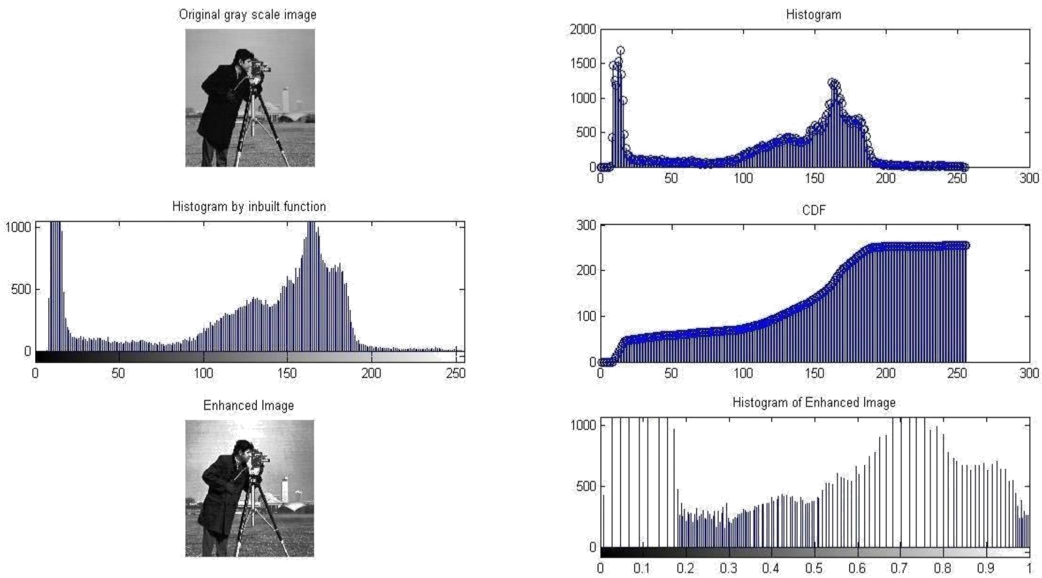


Figure 7: Histogram Equalization method

The above Figure (7) Histogram equalization means equal number of pixels in all the gray levels. Here our goal is to spread the dynamic extent, as well as to have parallel pixels in every grey level. It is done through cumulative density function.

2.3 Local Binary Enhancement

2.3.1 Introduction

Local Enhancement Histogram processing methods are global processing, in the sense that pixels are modified by a transformation function based on the gray-level content of an entire image. Histogram processing methods are global processing, in the sense that pixels are modified by a transformation function based on the gray-level content of an entire image. Sometimes, we may need to enhance details over small areas in an image, which is called a local enhancement. Sometimes, we may need to enhance details over small areas in an image, which is called a local enhancement.

Local Enhancement define a square or rectangular neighbourhood and move the center of this area from pixel to pixel. define a square or rectangular neighbourhood and move the center of this area from pixel to pixel. at each location, the histogram of the points in the neighbourhood is computed and either histogram equalization or histogram specification transformation function is obtained. at each location, the histogram of the points in the neighbourhood is computed and either histogram equalization or histogram specification transformation function is obtained. another approach used to reduce computation is to utilize nonoverlapping regions, but it usually produces an undesirable checkerboard effect. another approach used to reduce computation is to utilize nonoverlapping regions, but it usually produces an undesirable checkerboard effect.

The histogram processing methods discussed in the previous two sections are global, in the sense that pixels are modified by a transformation function based on the gray-level content of an entire image. Although this global approach is suitable for overall enhancement, there are cases in which it is necessary to enhance details over small areas in an image. The number of pixels in these areas may have negligible influence on the computation of a global transformation whose shape does not necessarily guarantee the desired local enhancement. The solution is to devise transformation functions based on the gray-level distribution or other properties in the neighbourhood of every pixel in the image.

The histogram processing techniques are easily adaptable to local enhancement. The procedure is to define a square or rectangular neighbourhood and move the center of this area from pixel to pixel. At each location, the histogram of the points in the neighbourhood is computed and either a histogram equalization or histogram specification transformation function is obtained. This function is finally used to map the gray level of the pixel centered in the neighbourhood.

2.3.2 Methodology

Arithmetic/Logic Operations

Enhancement using Arithmetic/Logic Operations Arithmetic/Logic operations perform on pixel by pixel basis between two or more images Arithmetic/Logic operations perform on pixel by pixel basis between two or more images except NOT operation which perform only on a single image except NOT operation which perform only on a single image as shown in figure (8).

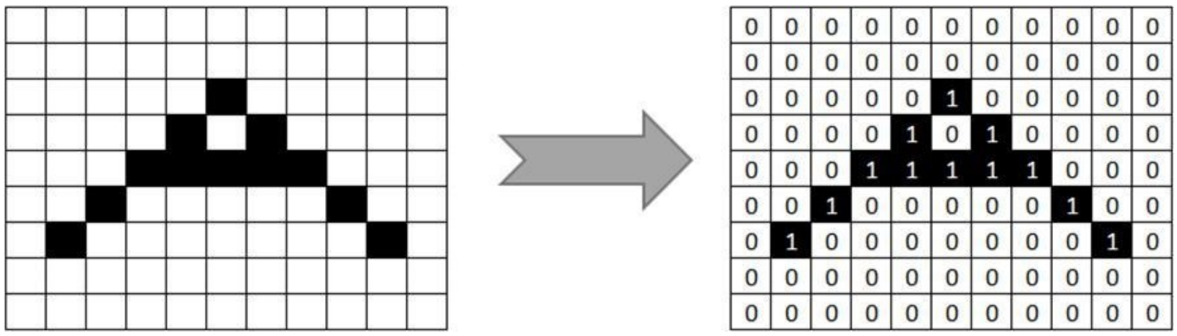


Figure 8: And representation

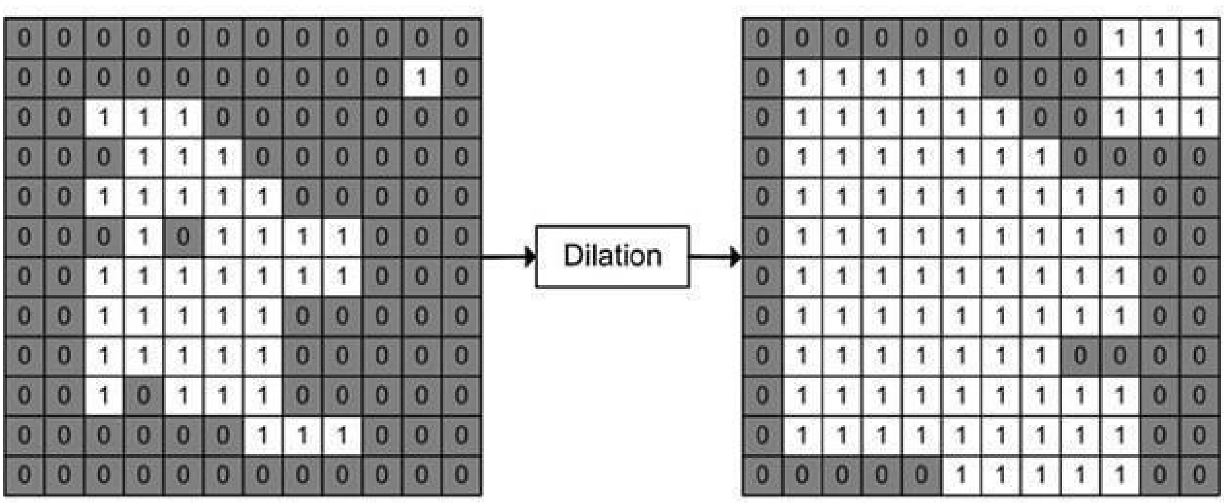


Figure 9: Dilation representation

In the above figure(9) the value of the output pixel is the maximum value of all pixels in the neighbourhood. In a binary image, a pixel is set to 1 if any of the neighbouring pixels have the value 1.

Morphological dilation makes objects more visible and fills in small holes in objects. Lines appear thicker, and filled shapes appear larger.

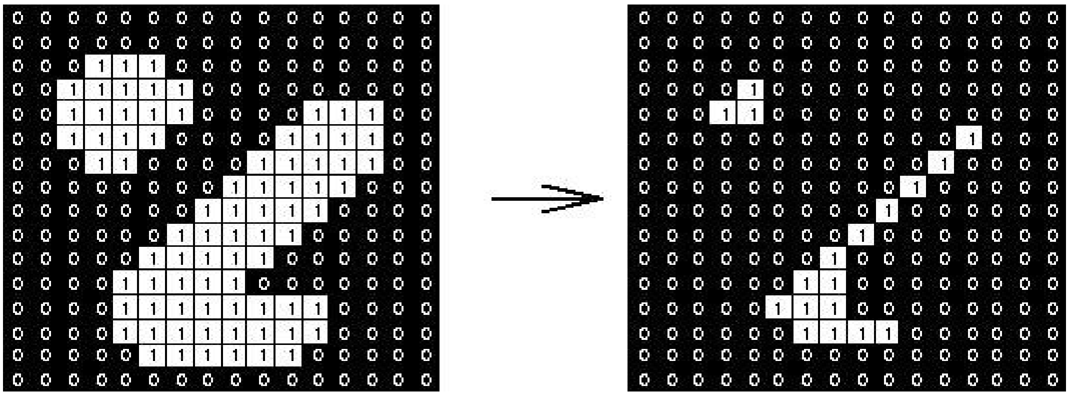


Figure 10: Erosion representation

The value of the output pixel in the Figure(10) is the minimum value of all pixels in the neighbourhood. In a binary image, a pixel is set to 0 if any of the neighbouring pixels have the value 0.

Morphological erosion removes floating pixels and thin lines so that only substantive objects remain. Remaining lines appear thinner and shapes appear smaller.

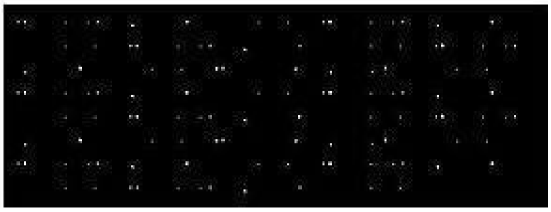
Open: In mathematical morphology, opening is the dilation of the erosion of a set A by a structuring element B:

$$A \circ B = (A \Theta B) \oplus B$$

Together with closing, the opening serves in computer vision and image processing as a basic workhorse of morphological noise removal. Opening can be used to find things into which a specific structuring element can fit (edges, corners, ...).

One can think of B sweeping around the inside of the boundary of A, so that it does not extend beyond the boundary, and shaping the A boundary around the boundary of the element.

Original image



Changed image

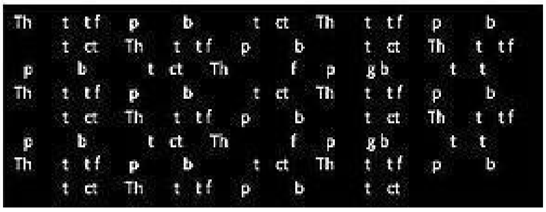


Figure 11: Image enhancement using open

In Figure (11) we can see Opening removes small objects from the foreground (usually taken as the bright pixels) of an image, placing them in the background, while closing removes small holes in the foreground, changing small islands of background into foreground. These techniques can also be used to find specific shapes in an image.

Closing

In mathematical morphology, the closing of a set (binary image) A by a structuring element B in the erosion of the dilation of that set

$$A¥B=(A\oplus B)\Theta B$$

In image processing, closing is, together with opening, the basic workhorse of morphological noise removal. Opening removes small objects, while closing removes small holes.

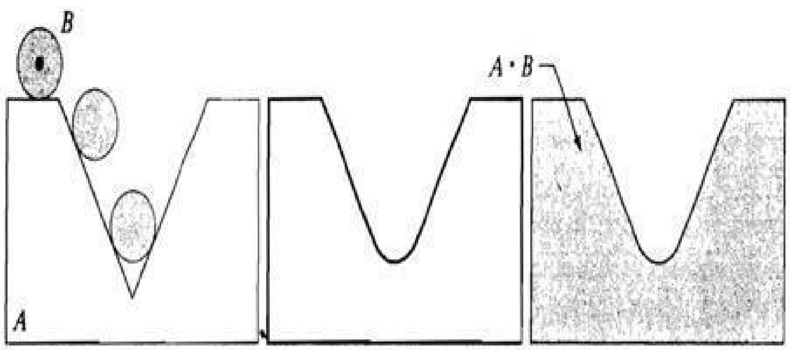


Figure 12: Image enhancement using closing

In Figure (12) we can see that Structuring element B "rolling" on the outer boundary of A. The heavy line is the outer boundary of the closing. Complete closing(shaded) portion is the closing part.

2.3.3 Results:

Local enhancement is used for only particular type of applications as show in the above figures. Although there are very crucial for building high complexity algorithms

Grey scale image Binay image(threshold) Errosion

Figure 13: Erosion, binary and grey image

In the above Figure(13) Erosion with small square structuring elements shrinks an image by stripping away a layer of pixels from both the inner and outer boundaries of regions. The holes and gaps between different regions become larger, and small details are eliminated

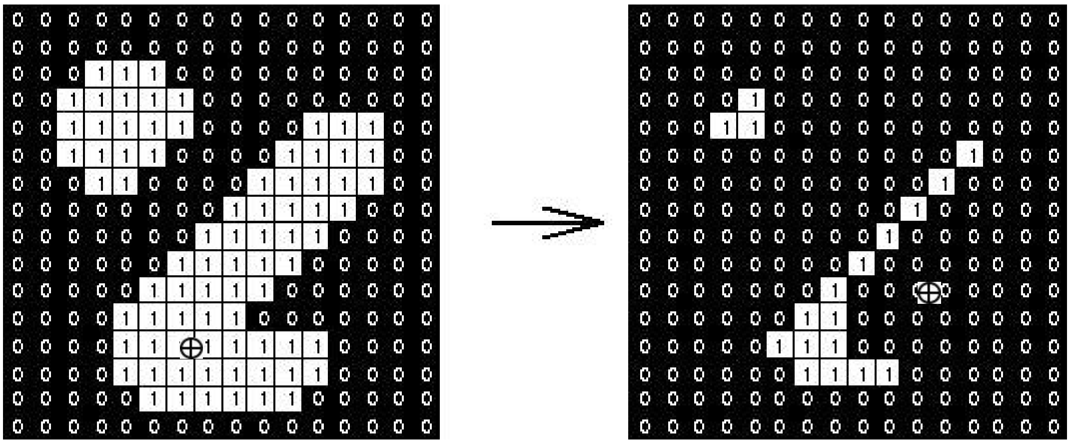


Figure 14: Erosion representation

In Figure(14) the 3×3 square is probably the most common structuring element used in erosion operations, The structuring element may have to be supplied as a small binary image, or in a special matrix format

Binary image Dilation

Fig 15: Images of binary and dilation enhancement

The dilation of an image in figure(15) f by a structuring element s produces a new binary image with ones in all locations (x, y) of a structuring element's origin at which that structuring element s hits the the input image f, i.e. g(x, y) = 1 if s hits f and 0 otherwise, repeating for all pixel coordinates (x, y). Dilation has the opposite effect to erosion it adds a layer of pixels to both the inner and outer boundaries of regions.

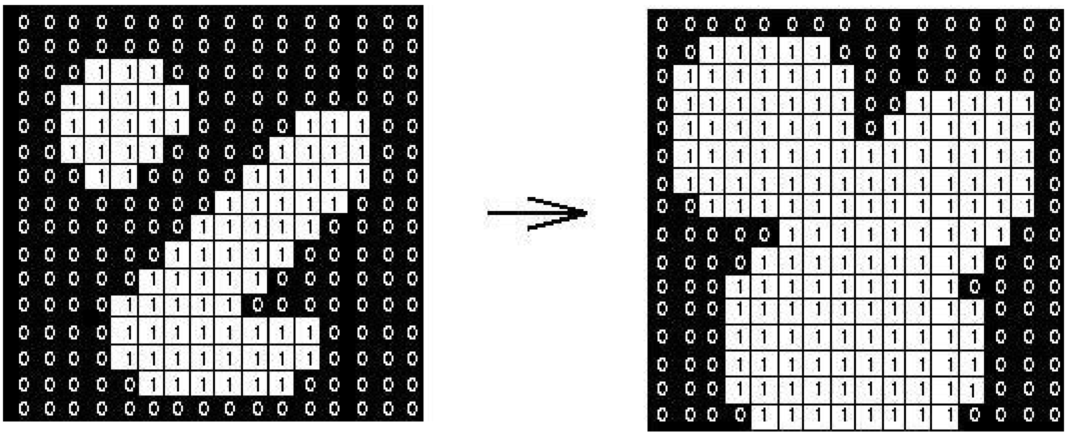


Fig 16: Dilation representation

The holes enclosed by a single region and gaps between different regions become smaller, and small intrusions into boundaries of a region are filled in Figure (16)

Chapter 3
Proposed Method
Contrast Enhancement Using 1D Histogram

The work has done in the arena of image enhancement. In this segment, Area of work done of the contrast enhancement is focus has been made on improve the quality of image.

3.1. Introduction:

Histogram equalization (HE), a simple contrast enhancement (CE) method, tends to show excessive enhancement and gives unnatural artifacts on images with high peaks in their histograms. Histogram-based CE methods have been proposed in order to overcome the drawback of HE, however, they do not always give good enhancement results.

The method is formulated as an optimization problem to preserve localities of the histogram for performing image CE. The locality-preserving property makes the histogram shape of the enhanced image to be similar to that of the original image. Experimental results show that the histogram-based method gives output images with graceful CE on which existing methods give unnatural results.

CONTRAST ENHANCEMENT (CE) techniques have been widely used for image enhancement in various applications. One of the most popular and simple CE techniques is histogram equalization. However, it has a severe problem that it gives unnatural effects or artifacts on some images with high peaks in their histograms. There are a lot of histogram-based CE algorithms that improve HE using various approaches. For example, bi-HE (BHE) is an algorithm that splits a histogram into two sub-histograms and applies HE to each sub-histogram. Brightness preserving BHE (BBHE) uses the mean intensity value of the input image to split its histogram. Minimum mean brightness error BHE (MMBEBHE) splits a histogram based on the absolute mean brightness error (AMBE). Brightness preserving dynamic HE (BPDHE) divides a histogram into several sub-histograms and applies HE to each sub-histogram separately, which is followed by the normalization that makes the contrast-enhanced image have the same mean intensity value as the input image. These existing histogram-based CE methods tend to preserve global average intensity value with the contrast of the whole image improved. There are other well-known methods that improve HE, however, they are parameter-sensitive which gives good quality only when the parameters are carefully chosen. In the meanwhile, CE using local statistical properties has been also studied. Adaptive HE (AHE) successfully takes local statistical properties into consideration and gives local details in the output images. However, it does not consider the global look of the images and the computational complexity is very high. Partially overlapped sub-block HE (POSHE) and cascaded multistep binomial filtering HE (CMBFHE) enhance AHE to consider overall look of the images and to decrease the computational complexity. However, these methods are still computationally expensive, which keeps them from commercial use.

CE method that preserves the locality of the histogram is proposed. The proposed method, so-called histogram-based locality- preserving CE (HBLPCE), solves an optimization problem to calculate an intensity transformation with the histogram of an input image. The objective function of the optimization problem is formed to find a least squares solution of locality conditions. The experimental results show that HBLPCE adapts well on images with various statistical properties

3.2. Proposed Work:

A. Locality Condition

Locality condition is defined using the intensity level in

image histogram. The purpose of the locality condition is to realize a local CE. By combining local CE at each intensity level, we form a global CE with the locality-preserving property, meaning that the local structure of the histogram is preserved after histogram processing.

In this letter, image histograms are described by the probability mass function (PMF), i.e., normalized histograms. Note that the sum of PMFs is equal to one. The PMF vector

p=[p1,p2,p3,_ _ _ ,p(n-1)]- probability mass function

r=[r1,r2,r3,_ _ _ , r(n-1)]- input intensity vector

x=[x1,x2,x3 _ _ _,x(n-1)]-transformed intensity

vector n indicates no of gray -level values

Locality condition at the transformed intensity level with respect to two neighbouring intensity levels is defined as

$$(x_i - x_{i-1})p_{i+1} = (x_{i+1} - x_i)p_i, \qquad \text{--eq(1)}$$

which represents that the histogram is stretched in inverse proportion to the PMF value in a local sense, as shown in The locality condition is designed to represent local structures of a stretched histogram. It is assumed that the two consecutive intensity difference (x(i)-x(i-1)) and (x(i+1)-x(i)) are stretched proportional to the PMF values (p(i+1) and p(i)), which maximizes the CE by giving larger intensity difference to larger PMF-valued intensity level, where the larger PMF-value also means larger number of pixels in that intensity level.

The locality condition can also be interpreted as local HE, in which the HE can be written as

$$x_i = (L-1)\sum_{k=0}^{i} p_k \qquad \text{--eq(2)}$$

$$x_{i+1} - x_i = (L-1)p_{i+1}. \quad \text{--eq(3)}$$

The recursive equation is equivalent to (1), obtained by combining two consecutive equations. If there are zero PMFs in the input histogram, the locality condition in (1) is modified as

$$w_{i,i-1}(x_i - x_{i-1})p_{i+1} = w_{i+1,i}(x_{i+1} - x_i)p_i, \quad \text{--eq(4)}$$

Where the weight factor

$$w_{i,j} = \exp(-(r_i - r_j)^2/2\sigma^2) \quad \text{--eq(5)}$$

2. **Optimization Problem Formulation**: To calculate, an optimization problem is formed in the context of locality conditions over the entire intensity range. The optimization problem using a least square method can be written as

$$\text{minimize} \sum_{i=1}^{N-2} [w_{i,i-1}(x_i - x_{i-1})p_{i+1} - w_{i+1,i}(x_{i+1} - x_i)p_i]^2 \quad \text{--eq(6)}$$

where L denotes the total number of intensity levels of the image, which equals 256 with 8-bit representation of the intensity level. The objective function is expressed in terms of the sum of squared errors of locality conditions over the entire intensity levels. Locality condition at each intensity level has a CE effect in a local sense and the objective function is formulated by combining locality conditions at all intensity levels over the entire intensity range of an input image. Two equality constraints represent that the enhanced image should use the full dynamic range, where and are the minimum and maximum intensity levels in the transformed image, respectively. Note that these two levels can be arbitrarily chosen by a user. The inequality constraint states that the intensity transformation should be a monotonically increasing function. The difference matrix be defined as

$$D = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & -1 & 1 & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & \ddots & \ddots & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & -1 & 1 & 0 & 0 \\ 0 & 0 & \cdots & 0 & -1 & 1 & 0 \\ 0 & 0 & \cdots & 0 & 0 & -1 & 1 \end{bmatrix},$$

where is an (N-1)*(N+1) matrix. By using the redefined x and D the optimization problem can be rewritten as

$$\text{minimize} \quad \mathbf{x}^T D^T Q D \mathbf{x} \quad \text{--eq(7)}$$

3. Solution of the Optimization Problem

To solve the optimization problem, is substituted by y=[x(1),x(2)-x(1),________x(N)-x(N-1)], where represents the difference vector between consecutive intensity levels in the transformed histogram where a tridiagonal matrix is formed with coefficients

$$\text{minimize} \quad \mathbf{y}^T Q \mathbf{y}$$

The optimization problem can be solved by using a general quadratic programming method.

3.3. Results:

The proposed HBLPCE is tested on various colour images with different statistical properties and compared to existing HE, BPDHE, BBHE, MMBEBHE, and recursively separated and weighted HE (RSWHE) methods. The parameters of RSWHE method are chosen based on the authors' suggestion. The proposed method is compared with global CE methods only because local ones give very different tendency and are hard to compare with. In this letter, each CE method is realized in HSV colour space, manipulating the V channel with the H and S channels unchanged. HSV colour space is chosen to avoid colour distortion in enhanced images. HBLPCE can also be performed in YCbCr, YUV, and Lab color spaces. The user-controllable parameter that adjusts the weight factor is experimentally set to 10.

The below figure shows experimental results with their histograms. The top left image is an original image (kodim02.png) with a unimodal histogram. Compared to other methods, RSWHE and the proposed HBLPCE produce histograms of which the shape is similar to that of the original histogram. The locality-preserving property on histogram gives a shape-preserving result while histogram stretch can also be observed, whereas RSWHE gives weaker histogram stretches. The result images of HE, BPDHE, BBHE, and MMBEBHE show rather excessive CE, which lead to unnatural artifacts in the contrast-enhanced images. On the other hand, HBLPCE shows a graceful CE with a natural contrast-enhanced image.

The left image in the second row is an original image (kodim03.png) with a multimodal histogram. The histograms of MMBEBHE, RSWHE, and HBLPCE results are similar to the original histogram compared to the histograms of the other methods. HE, BPDHE, and BBHE give somewhat excessive CEs, which make details of the images hardly observed (see the top of the yellow cap and the texture in the wood board against the wall). The result images of MMBEBHE and HBLPCE show better enhanced results while details in the images are well-preserved.

An extremely dark original image (moon.bmp) with a left skewed histogram is illustrated on the left in the third row. HE gives an excessive CE and shows a severe colour distortion. BPDHE fails to enhance the contrast of the input image while preserving the mean intensity value. BBHE and MMBEBHE produce acceptable contrast-enhanced images, however these methods do not preserve details in the bottom of the images. On the contrary, HBLPCE and RSWHE give graceful CEs and preserves details in the bottom (around the rocks between a man and vehicle).

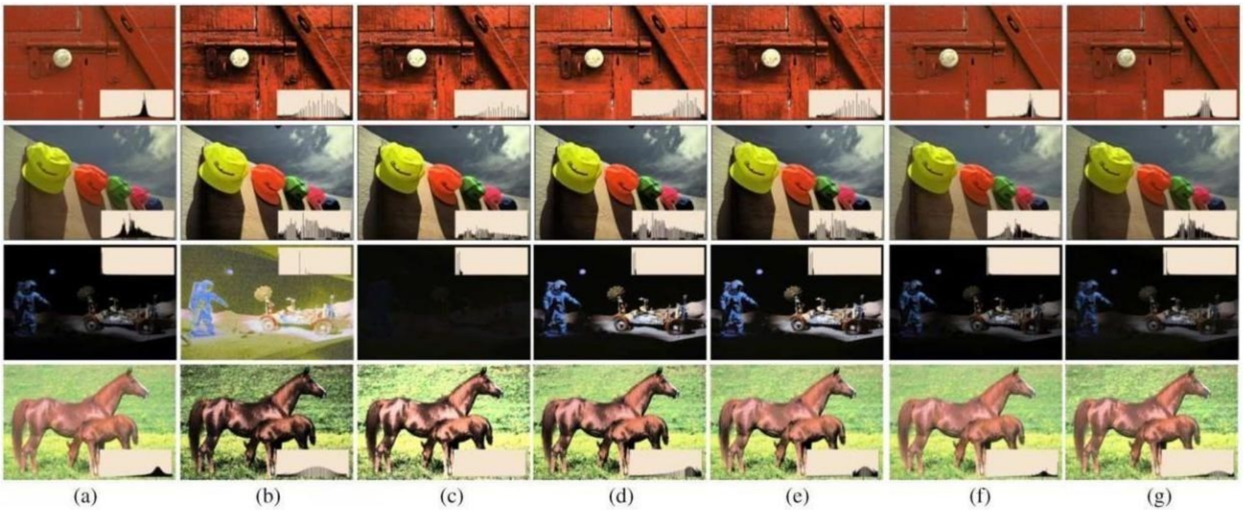


Figure 17: Experimental results on kodim02.png, kodim03.png, moon.bmp, and horse.jpg images (from top to bottom), (a) original image, (b) HE, (c) BPDHE, (d) BBHE, (e) MMBEBHE, (f) RSWHE, (g) one dimensional histogram.

A saturated original image Figure(17) (horse.jpg) is shown at the bottom left. The PMF shows its highest value at the highest intensity value, which is caused by saturation in the image. HE gives a too dark image. BPDHE gives a much lighter image, saturating the result image much further. RSWHE does not show a significant change in the output image. BBHE and MMBEBHE produce unnatural results, while PMF of the result images are unnaturally dense at some intensity levels. The proposed HBLPCE gives a very natural-looking image. The enhanced image reveals a lot of details in the background regions and the body of the horses. Additional experiments show that the proposed HBLPCE gives better contrast-enhanced results for images with multimodal histograms as well.

Table 1 shows quantitative comparisons on the four test images. AMBE, contrast improvement index (CII), and discrete entropy are used as measures of CE. AMBE is defined as the absolute difference of the mean intensity between the original and the contrast enhanced images. If AMBE is small, the average brightness of the image is well preserved. The local contrast is computed as

$$C_{\mathrm{local}} = \frac{\max - \min}{\max + \min},$$

where max and min represent the maximum and minimum intensity values. In the case of both max and min values are zeros.

Table1: Objective assessment on various images by comparing with 1d histogram

Image	Method	AMBE	CII	*H*	HI
kodim02.png	Original	N/A	N/A	6.24	N/A
	HE [1]	12.5	4.34	6.01	0.11
	BPDHE [4]	0.9	3.84	5.63	0.14
	BBHE [2]	18.3	3.04	6.04	0.20
	MMBEBHE [3]	0.4	3.92	6.02	0.14
	RSWHE [7]	0.5	1.29	6.19	0.78
	HBLPCE	10.0	1.53	6.11	0.54
kodim03.png	Original	N/A	N/A	7.24	N/A
	HE [1]	10.0	2.18	7.02	0.39
	BPDHE [4]	0.4	1.93	6.92	0.46
	BBHE [2]	3.8	2.37	7.03	0.43
	MMBEBHE [3]	0.6	2.33	7.02	0.42
	RSWHE [7]	2.2	1.31	7.20	0.79
	HBLPCE	10.0	1.29	7.17	0.72
moon.bmp	Original	N/A	N/A	4.15	N/A
	HE [1]	134.5	0.32	3.89	0.00
	BPDHE [4]	0.3	0.30	2.92	0.04
	BBHE [2]	21.7	0.43	3.83	0.11
	MMBEBHE [3]	21.4	0.43	3.81	0.10
	RSWHE [7]	1.1	0.47	3.85	0.66
	HBLPCE	6.1	0.88	4.04	0.49
horse.jpg	Original	N/A	N/A	7.05	N/A
	HE [1]	64.7	3.22	6.85	0.36
	BPDHE [4]	11.3	2.53	4.89	0.23
	BBHE [2]	18.3	2.29	6.80	0.53
	MMBEBHE [3]	7.3	1.73	6.78	0.64
	RSWHE [7]	1.3	1.13	6.97	0.92
	HBLPCE	6.9	1.38	6.81	0.61

In Table(1) BPDHE and MMBEBHE aim to minimize AMBE, which preserve the average intensity of the original image, however, they do not guarantee better enhanced results. BBHE gives larger CII than HE does on kodim03.png, meaning that it fails to reduce excessive CE by HE. RSWHE shows the largest HI values, which indicates that the shape of the histogram is well-preserved, however the result images do not show significant differences from the original ones. HBLPCE gives lower CII values than other methods, however the CII values are more stable than those of other methods. Other methods except for RSWHE give varying CII value, which indicates that their CE performance varies from the statistical properties of the input images. HBLPCE also gives moderate and stable AMBE and HI values, showing better trade-offs than other methods.

Table 2: Execution time on different algorithms

Method	Execution time (ms)		
	768×512	2048×1080	4096×2160
HE [1]	11	61	349
BPDHE [4]	15	64	357
BBHE [2]	12	67	380
MMBEBHE [3]	26	123	626
RSWHE [7]	13	71	386
CMBFHE [10]	1013	1992	5596
HBLPCE	40	97	385

The execution times on different size images are shown in above Table 2. The experiment performed on 20 images on each resolution and the average execution time is shown. All CE methods are tested on Core i5 processor using MATLAB. The proposed HBLPCE is compared with the global CE methods and CMBFHE. CMBFHE is a local CE method, which implements well-known POSHE very efficiently with the identical results. CMBFHE takes much longer time than global CE methods, which increases drastically with the size of the input image. HBLPCE takes the longest time among the global CE methods for small images, while the execution times of global CE are similar for large images.

Chapter 4
Contrast Enhancement Using 2D Histogram

4.1. Introduction:

Contrast Enhancement Algorithm based on the layered difference representation of 2D histograms. It attempts to enhance image contrast by amplifying the gray-level differences between adjacent pixels. To this end, it obtain the 2D histogram h(k, k + l) from an input image, which counts the pairs of adjacent pixels with gray-levels k and k + l, and represent the gray-level differences in a tree-like layered structure. Then, we formulate a constrained optimization problem based on the observation that the gray-level differences, occurring more frequently in the input image, should be more emphasized in the output image. We first solve the optimization problem to derive the transformation function at each layer. We then combine the transformation functions at all layers into the unified transformation function, which is used to map input gray levels to output gray-levels.

In spite of recent advances in imaging technology, captured images often fail to preserve scene details faithfully or yield poor contrast ratios due to limited dynamic ranges. Contrast enhancement (CE) techniques can alleviate these problems and bring out hidden details. CE is an essential step in various image processing applications, such as digital photography, video communications, and visual surveillance, and a lot of researches have been made to develop efficient CE techniques.

Conventional CE techniques can be categorized into global and local approaches. A global approach derives a single transformation function, which maps input intensities to output intensities, and applies it to all pixels in an entire image. For example, the gamma correction based on the simple power law is a well-known CE technique. On the other hand, a local approach, It derives and applies the transformation function for each pixel adaptively according to the information in a local neighbourhood. However, in general, a local approach demands higher computational complexity and its level of CE is harder to control. Therefore, being more stable, global CE techniques are more widely used in practical applications. Histogram specification which attempts to obtain the output histogram of a desired shape, is a global CE technique. However, there is no obvious choice for the desired histogram, since natural images exhibit significantly different histogram characteristics from one another. Thus, simple mathematical distributions, such as uniform, Gaussian, or exponential, are typically used as the desired histograms. Especially, when the uniform distribution is used, HS is referred to as histogram equalization HE is one of the most widely adopted techniques to enhance low contrast images due to its simplicity and effectiveness

However, it has some drawbacks, such as contrast over-stretching, noise amplification, or contour artifacts. Various researches have been made to overcome these drawbacks. For example, several algorithms divide an input histogram into sub-histograms and equalize them independently to reduce the brightness change between input and output images. Also, histogram modification (HM) techniques, which manipulate an acquired histogram before the equalization, have been introduced. Some algorithms clamped large histogram values and then modified the resulting histogram using the power law. It employed a logarithm function to reduce large histogram values effectively, preventing the transformation function from having too steep slopes. Several researches also have been carried out to extend the conventional HE to the multidimensional histograms of colour images. A generalized HE to enhance the contrast of colour images and developed an algorithm to avoid the gamut problem during the enhancement. The iso-luminance HE algorithm for enhancing RGB images, which achieves the uniform histogram of the luminance channel.

These global CE techniques process the histograms of input images to obtain output images. The histogram processing has the advantages of straightforward implementation and computational efficiency, since it achieves significant data reduction. However, it discards the spatial information in the unordered summarization process. In other words, the histogram cannot capture the joint relationships between neighbouring pixels. Recently, a few CE algorithms have been developed to consider spatial image features by extending the notion of the histogram.

The histogram of an input image adaptively to image characteristics. They reduced large histogram values for smooth areas corresponding to background regions to focus on the enhancement of foreground objects. However, their algorithm does not use the joint relationships between pixels explicitly for the enhancement. In another algorithm it has constructed a 2D histogram, which recorded the numbers of gray-level pairs in an input image, and modified it to emphasize large gray level differences. Then, they achieved CE by mapping the diagonal elements of the 2D input histogram to those of the 2D modified histogram. However, their mapping scheme may not handle large histogram values appropriately and may yield over-stretching artifacts.

Novel global CE algorithm based on the layered difference representation (LDR). The algorithm also uses a 2D histogram, but adopts a different theoretical approach. First obtain the 2D histogram of gray-level differences between neighbouring pixels ad then attempt to amplify gray-level differences, occurring frequently in the input image, to enhance the contrast. To this end, it represent output gray-level differences and the transformation function in a tree-like layered structure. This representation is called the LDR. Then, at each layer, it formulates a constrained optimization problem for the enhancement and solve it efficiently to obtain the difference vector. Finally, we aggregate the difference vectors at all layers into a single unified difference vector, which is equivalent to the transformation function. Extensive experimental results demonstrate that the proposed algorithm yields higher image qualities than the conventional HE

4.2. Methodology:

Algorithm has two main components:

intra-layer optimization and inter-layer aggregation.

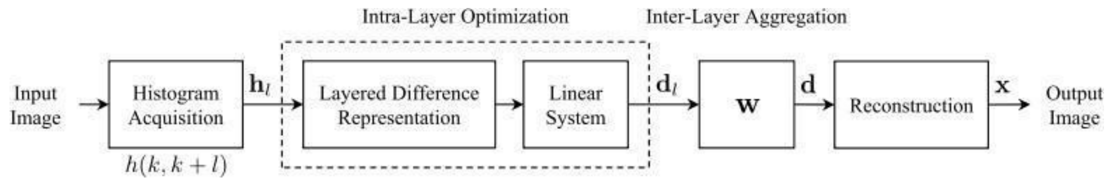


Fig 18: Block diagram of 2D histogram

We first extract a 2D histogram h(k, k + l) from an input image, by counting the pairs of adjacent pixels with gray-levels k and k + l. In the intra-layer optimization, we obtain the histogram vector hl at each layer l and use it to formulate a system of linear equations. By solving the system, we obtain the difference vector dl at layer l as shown in the figure(18). Next, in the interlayer aggregation, we combine the difference vectors at all layers into the unified difference vector d using the weighting vector w. We then reconstruct the transformation function x from d and transform the input image to the output image

Since the human visual system (HVS) is more sensitive to gray-level differences between neighbouring pixels than to absolute gray-levels, we can achieve perceptual CE by emphasizing the differences. However, most enhancement algorithms focus on the first-order distribution of absolute gray-levels in an image, without considering the spatial placement of those gray-levels nor the joint gray level distribution of neighbouring pixels. Therefore, these conventional algorithms may fail to provide visually satisfying images.

To clarify differences between the conventional algorithms and the proposed algorithm, it perform tests on a synthetic Image above, which has four overlapping squares with different gray-levels. As shown in the normalized histogram

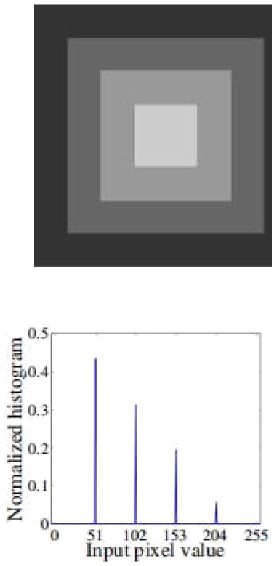


Figure 19: Intial synthetic image

In the above figure(19) does not exploit the full dynamic range and its gray-levels are confined to the range of [51, 204].

To enhance the contrast, the gray-level distribution should be stretched to the full dynamic range: the lowest and the highest gray-levels in the input histogram should be mapped to the minimum and the maximum gray-levels, respectively. However, this cannot be achieved by the conventional algorithms. HE causes a steep slope in the transformation function, when a histogram bin has a large value. In this example, the lowest gray-level,51, composes more than 40% of the input image.

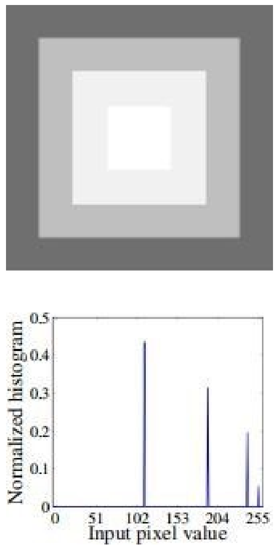


Figure 20: HE synthetic image

In the above figure(20) HE hence makes the lowest gray-level even brighter, degrading the quality of the output image in above figure.

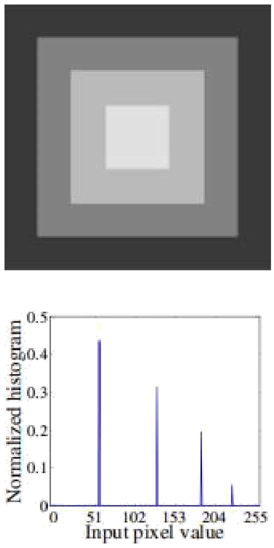


Figure 21: WAHE Synthetic image

In the above figure(21) WAHE alleviates the over-enhancement problem in HE and maintains a similar dynamic range to the input image. But, it fails to achieve further enhancement. To the best of our knowledge, CVC was the first CE algorithm, which adopted a 2D histogram to use the contextual information in an image, such as edges and object boundaries. However, it does not fully exploit the relationship between input gray-level differences and output gray-level differences.

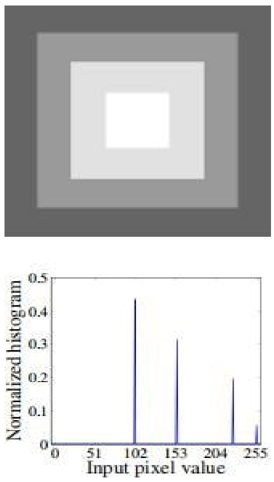


Fig 22: CVC synthetic image

CVC reduces the contrast as shown in the above figure(22).

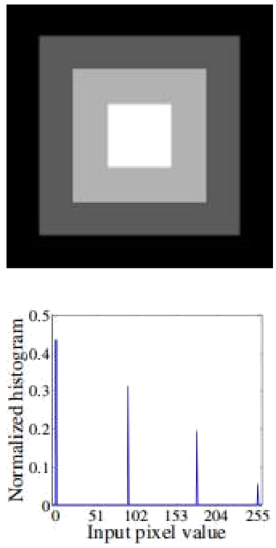


Figure 23: Proposed Synthetic Image

On the contrary in the above figure(23), the algorithm considers the statistics of gray-level differences, instead of absolute gray levels, and derives a desirable relationship between the 2D histogram of the input image and the gray-level differences in the output image. Consequently, the gray-level differences, which occur frequently across the square boundaries in the input image, are amplified in the output image to improve the contrast. Above figure(20) shows that the algorithm exploits the full dynamic range and outputs a higher contrast image than the conventional algorithms.

A. Intra-Layer Optimization:

Given the 2D histogram $h^l{}_k$of the input image in $h^l{}_k = \log(h(k, k + l) + h(k + l, k)), 0 \leq k \leq 255$
we should decide the difference variables d1k 's at layer 1, which satisfy the equations in
$dlk = kl \times hl(k), 0 \leq k \leq 255 - l$

We can solve this over-determined system with the non-negative constraint based on the Non-Negative Least Squares (NNLS) technique. NNLS, which considers all layers in a single system which yields an undesirable solution and also sensitive to magnitude variations in the 2D histogram.

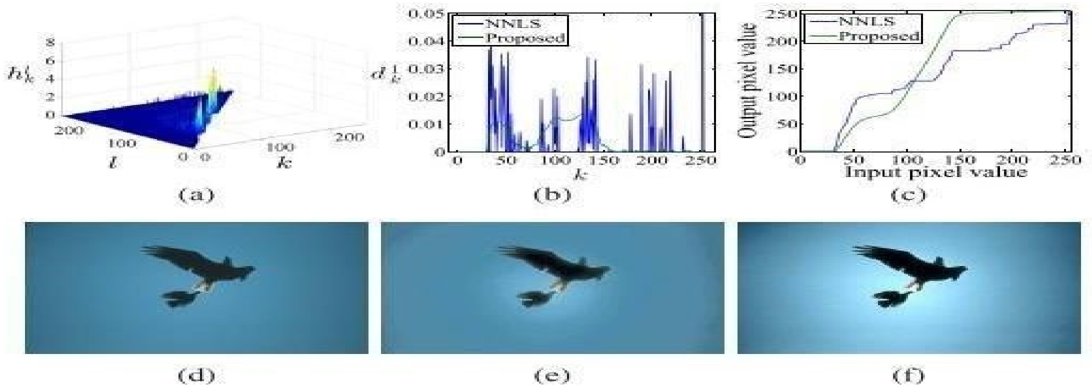


Figure.24 The enhancement of the "Eagle" image. For better evaluation of image qualities, we recommend the readers to see this figure on display devices rather than the printed version. (a) 2D histogram. (b) Difference vector. (c) Transformation function. (d) Input. (e) NNLS. (f) Proposed.

For example, In the above Figure 24 (a) shows the histogram h_k^1 for an input image in Fig24 (d). Histogram components around h^1_3 and h^1_{10} are much larger than the others. In the least square's optimization, the sum of the squared errors is dominated by these large components. As a result, the other histogram components contribute little to the solution and the difference variables in Fig 24(b) are irregular and noisy. Therefore, the transformation function in Fig.24(c) is not smooth and causes contour artifacts in the output image in Fig.24 (e).

The example in the above Fig. indicates that it is necessary to process the information at each layer separately. We then aggregate the separate solutions for different layers to form the overall solution. Fig.24 (f) shows that the proposed algorithm provides a higher quality image with less contour artifacts than the NNLS technique. At each layer l, d_k^1 are determined by the 2D histogram values $h^1{}_k$.

B. Inter-Layer Aggregation:

The intra-layer optimization at each layer, we obtain 255 difference vectors d_l's, $1 \leq l \leq 255$. We aggregate these difference vectors to form a unified difference vector d. We obtain d_l from the histogram of pixel pairs, whose gray-level differences are l. For a typical input image, most elements in hl are zero when l is large. In other words, hl becomes sparser as l gets larger. The reliability of dl is proportional to sl

In the above Fig. shows s_l's for various test images, which are normalized by the maximum values. We see that, as l increases, the occurrence frequency s_l gets lower. Therefore, d_l at a higher layer l has a less impact on the unified difference vector d.

We first normalize s_l’s to w_l’s by dividing it with the maximum value and applying a simple power law function with a user-controllable parameter α. Then, we obtain the unified difference vector d by d = $(1 \div 1^T w)Dw$.

Then first normalize sl’s to wl’s by dividing it with the maximum value and applying a simple power law function with a user-controllable parameter α. Specifically, we obtain the weighting vector w = [w1, w2,··· , w255] T, whose lth element is given by wl = (sl ÷ maxi si)α .Then, we obtain the unified difference vector d by d = (1÷1w(T))Dw, (24) where D ∈ R255×255 is a concatenated matrix whose ith column is di . Finally, we obtain the transformation function x from the unified difference vector d. The algorithm considers the statistics of gray-level differences, instead of absolute gray levels, and derives a desirable relationship between the 2D histogram of the input image and the gray-level differences in the output image. Consequently, the gray-level differences, which occur frequently across the square boundaries in the input image, are amplified in the output image to improve the contrast.

4.3 Results and Discussion

Here it selects test images of resolution 768x512 from the Kodak Lossless True Color Image Suite test images of resolution 512x512 from the USC-SIPI Database, test images of resolution 481x312 from the Berkeley Image Data Set, and test images captured from commercial digital cameras. In total, we use 600 test images. It compare the proposed algorithm with the conventional HE, WAHE and CVC algorithms. For WAHE, the parameter *g* is fixed to 1.5 to yield the best overall image quality. For CVC, the parameters are set to α β γ 1⁄3 and the 7 7 neighborhood is used, as suggested. In the proposed algorithm, the only controllable parameter is α. We fix α to 2.5 in all experiments to provide the best overall performance in terms of the objective quality metrics, which will be explained. It processes luminance components only in the experiments. Specifically, given acolor image, we convert it to the YUV color space, and then process only the Y component without modifying the U and V components.

A. Objective Assessment

Table 3: Objective quality assessment on various algorithm

	Input	HE	WAHE	CVC	Proposed
DE	7.11	6.91	<u>7.05</u>	7.04	**7.07**
EME	18.89	**31.65**	19.04	29.33	<u>30.32</u>
AMBE	-	30.04	**10.23**	<u>12.28</u>	13.13
PixDist	28.08	**42.21**	33.93	34.75	<u>36.70</u>

In Table(3) We assess the CE performance objectively using four quality metrics: discrete entropy (DE), measure of enhancement (EME), absolute mean brightness error (AMBE), and PixDist. Table I lists the average performance on the 600 test images. For each metric, the best and the second best results are boldfaced and underlined, respectively in table 3.

First, DE measures the amount of information in an image: a high DE indicates that the image contains more variations and conveys more information. Because of the information processing inequality, no output image, processed by any transformation function, can have a higher DE than the input image. Thus, the proposed algorithm provides a lower average DE than the input, the proposed algorithm conveys more information than all the conventional algorithms.

Second, EME approximates the average contrast in an image by dividing the image into blocks, computing a score based on the minimum and the maximum gray-levels in each block, and averaging the scores. The block size is set to 8 × 8 in this experiment. HE provides the best EME score, but it causes over-stretching or over-enhancement artifacts, as will be illustrated in the next section.

Since CVC and the proposed algorithm exploit the 2D contextual information and enhance local details efficiently, they yield significantly better EME scores than WAHE. Third, AMBE measures the absolute difference between input and output gray-level means. A lower value implies that the corresponding algorithm well preserves the mean brightness of an input image.

WAHE incurs the lowest brightness change, since it reduces the abnormality by averaging its transformation function with the linear transformation function. The proposed algorithm ranks third. However, WAHE, CVC, and the proposed algorithm provide similar AMBE scores, which are significantly better than the score of HE. Fourth, PixDist computes the average gray-level difference over all pixel pairs in an image. It yields a high score when histogram components are uniformly distributed without concentrating at particular gray-levels. Except for the contrast over-stretching HE algorithm, the proposed algorithm provides the best performance in terms of PixDist.

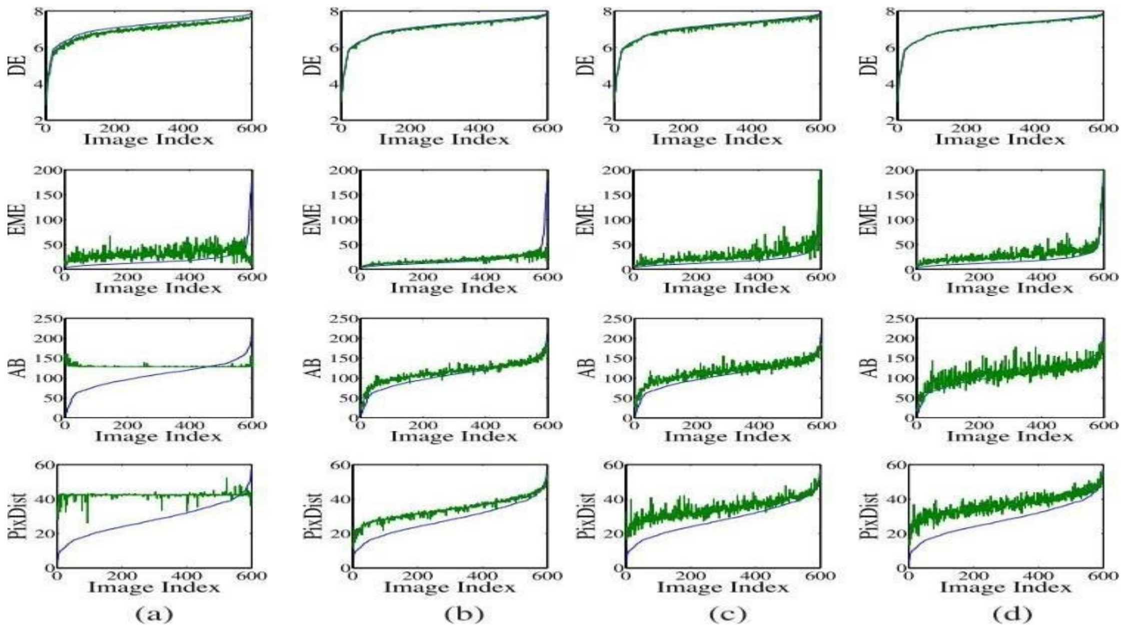


Figure.25 Objective metric scores on 600 test images. From top to bottom, the four rows plot the DE, EME, average brightness (AB), and PixDist scores. The measurements from the input images are plotted in blue, whereas those from the enhanced images are displayed in green. (a) HE. (b) WAHE. (c) CVC, (d) Proposed.

To evaluate the performance variations on individual test images, we plot the metric scores of output images in comparison with those of input images in above Figure (25). In each graph, the 600 input images are indexed so that their scores are sorted in the ascending order. For DE, the proposed algorithm provides the best performance, which is very close to the input curve. For EME, the proposed algorithm enhances the score of every input image.

In contrast, the conventional algorithms reduce the scores of some input images, especially when the input scores are high. In the case of AMBE, the average brightness (AB) is plotted instead of the brightness error. The proposed algorithm causes bigger variations in AB than the conventional algorithms, since it is more adaptive to local image details and structures. For PixDist, the proposed algorithm increases the score of every input image.

A. Subjective Assessment

Even though an image provides a higher objective quality score than another image, its subjective visual quality is not always superior accordingly. In this section, we provide examples of output images to assess their qualities subjectively and analyse the characteristics of the proposed algorithm in comparison with those of the conventional algorithms.

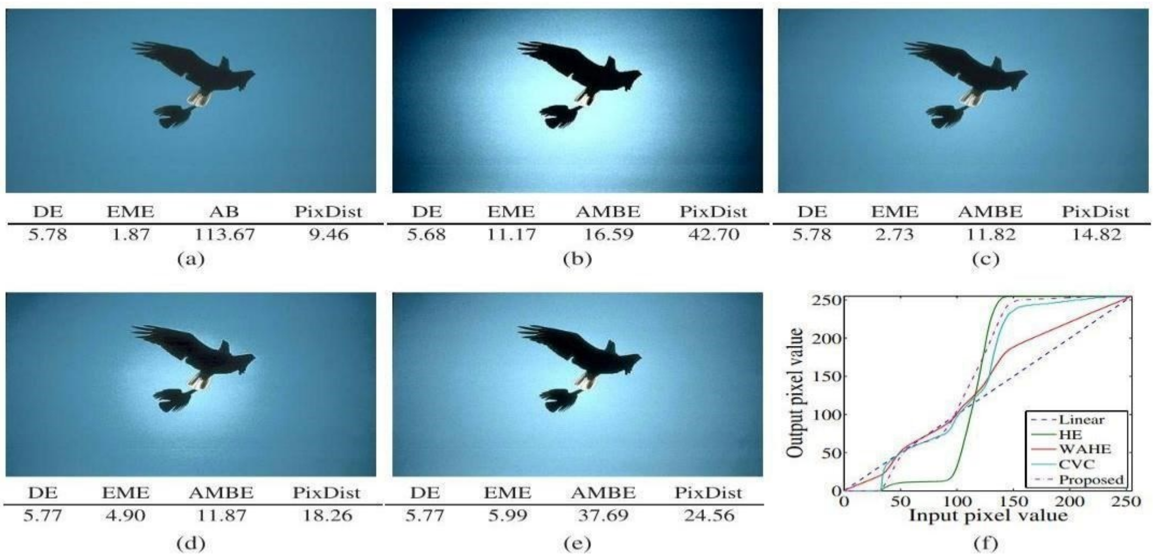


Figure.26 CE results on the “Eagle” image: (a) input image, (b) HE, (c) WAHE, (d) CVC, (e)the proposed algorithm, and (f) the comparison of the corresponding transformation functions.

In above Figure (26). shows the CE results on the “Eagle” image, which is mainly composed of a sky region with similar gray-levels in the range of [100, 140]. This region causes a high peak in the input histogram, which HE and CVC cannot handle properly. More specifically, HE and CVC yield steep slopes in their transformation functions, when the input gray-level is between 100 and 140, as shown in Figure(26) (f).

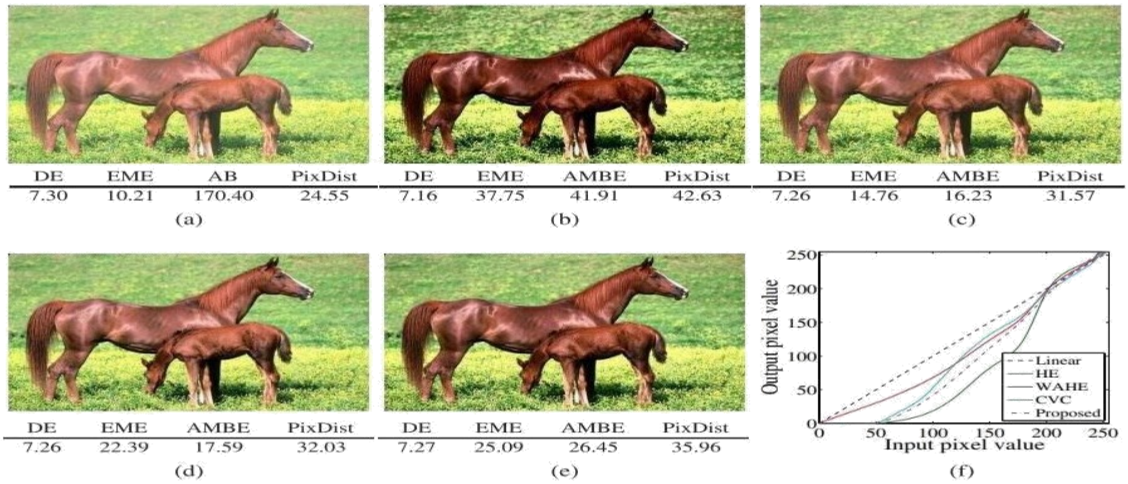


Figure.27 CE results on the “Horse” image: (a) input image, (b) HE, (c) WAHE, (d) CVC, (e) the proposed algorithm, and (f) the comparison of the corresponding transformation functions.

In figure(27) HE and CVC increase the contrast on the smooth region excessively, producing contour artifacts. Both WAHE and the proposed algorithm effectively reduce the histogram peak and suppress the contour artifacts. Furthermore, compared with WAHE, the proposed algorithm provides a more distinctive silhouettes of the eagles and better local contrast on the eagle’s tail. In this example, the minimum input gray-level is 23.

WAHE expresses the darkest pixels less darker than the other algorithms by starting its output gray-level from 14. Therefore, WAHE uses a narrower output dynamic range, yielding the lowest EME score. On the contrary, the proposed algorithm exhibits better contrast by exploiting the full dynamic range.

In the above Figure 27 shows the CE results on the hazy “Horse” image. HE achieves the highest EME by removing the hazy components, but it also causes the largest AMBE as it darkens pixel intensities severely. WAHE does not transform the darkest input gray-level, which is 40 in this example, to the pure black level 0.

Also, WAHE transforms the input gray-levels between [50, 100], which correspond to the foreground horses, with a lower increasing rate than the linear function. Therefore, it does not enhance the details on the horses clearly. Both CVC and the proposed algorithm exploit the entire dynamic range, but the proposed algorithm amplifies the gray-level differences within the horses more effectively and provides a better image quality.

In case of the “Island” image in Figure(27). 10, the original image looks dull due to its low contrast. HE and CVC improve the visual quality of the input image, but they incur over enhancement problems. While they boost gray-levels within [100, 250], they lose the details in the clouds and change the overall brightness dramatically from the input image.

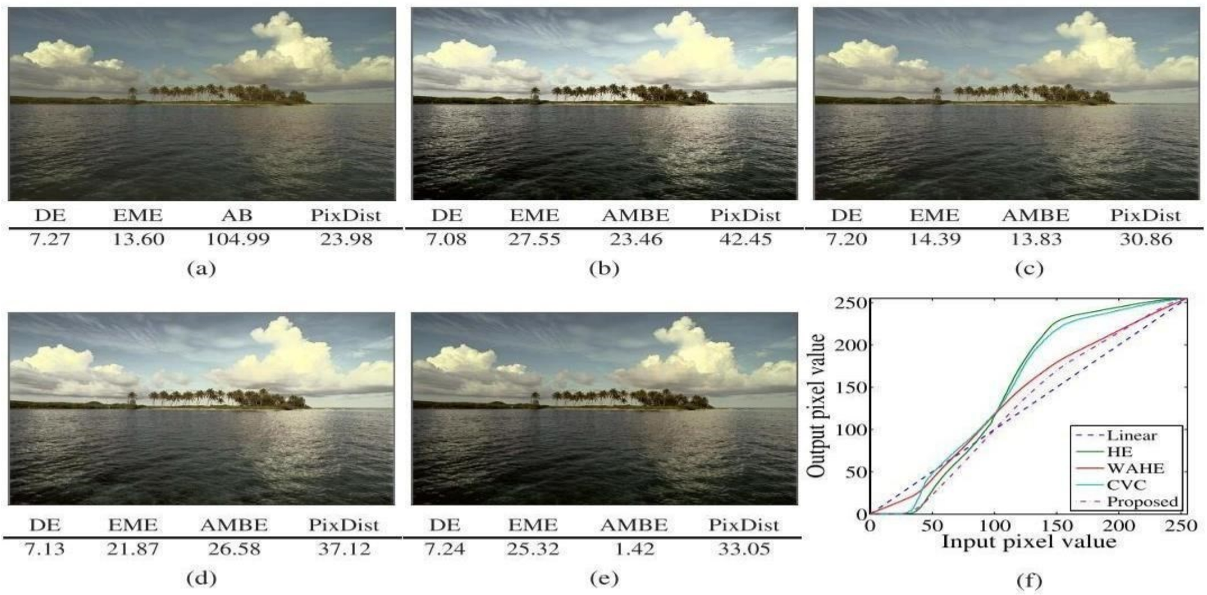


Figure.28 CE results on the “Island” image: (a) input image, (b) HE, (c) WAHE, (d) CVC, (e) the proposed algorithm, and (f) the comparison of the corresponding transformation functions. In figure(28) WAHE and the proposed algorithm provide comparable image qualities in this example. However, the proposed algorithm enhances the dark seawater more vividly, without losing details in the bright cloud regions. Digital images often fail to capture scene details faithfully due to limited dynamic ranges or unideal imaging systems.

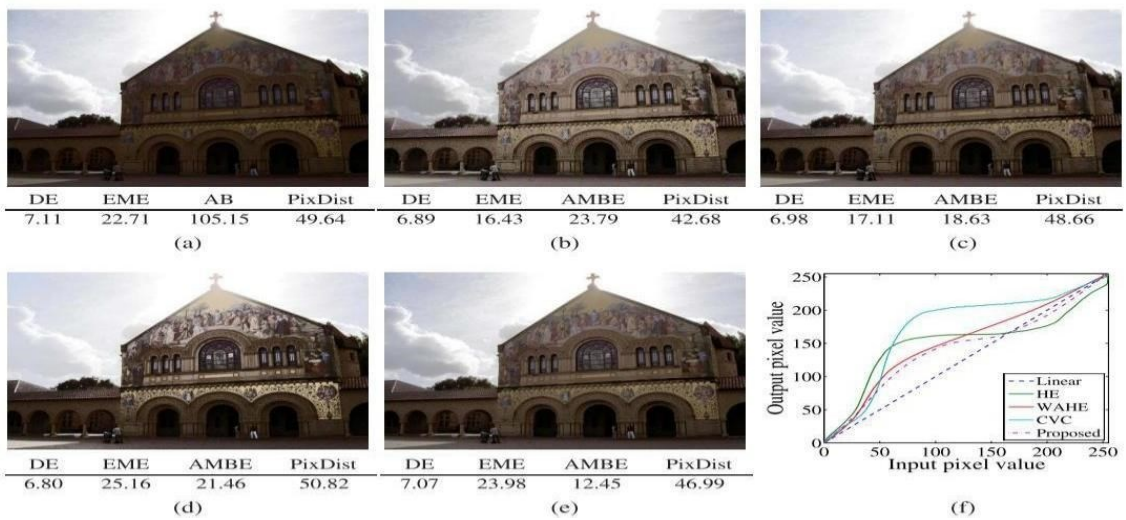


Figure.29 CE results on the “Memorial Church” image: (a) input image, (b) HE, (c) WAHE, (d) CVC, (e) the proposed algorithm, and (f) the comparison of the corresponding transformation functions.

In the following tests, we use test images that are acquired in those poor environments.In Figure(29) First, most imaging systems cannot capture object details clearly when very bright and very dark regions coexist in the same scene. In such a case, an acquisition system selects the exposure setting for either bright or dark region only. In the above Figure(29). shows an example of a low exposure setting, which is selected to capture the bright sky area faithfully and thus degrades the details in the dark facade of the church. HE obtains the transformation function based on the 1-D histogram, without considering gray-level differences between neighbouring pixels. Therefore, it over-stretches the contrast of the smooth sky region and causes contour artifacts. CVC maps input gray-levels [30, 80] to output gray-levels [50, 200] to enhance the contextual features such as the paintings on the wall. However, the dramatic contrast increase on this region alters the mood of the photograph undesirably. WAHE and the proposed algorithm provide more reliable CE results than HE and CVC, without the excessive alteration of the input image.

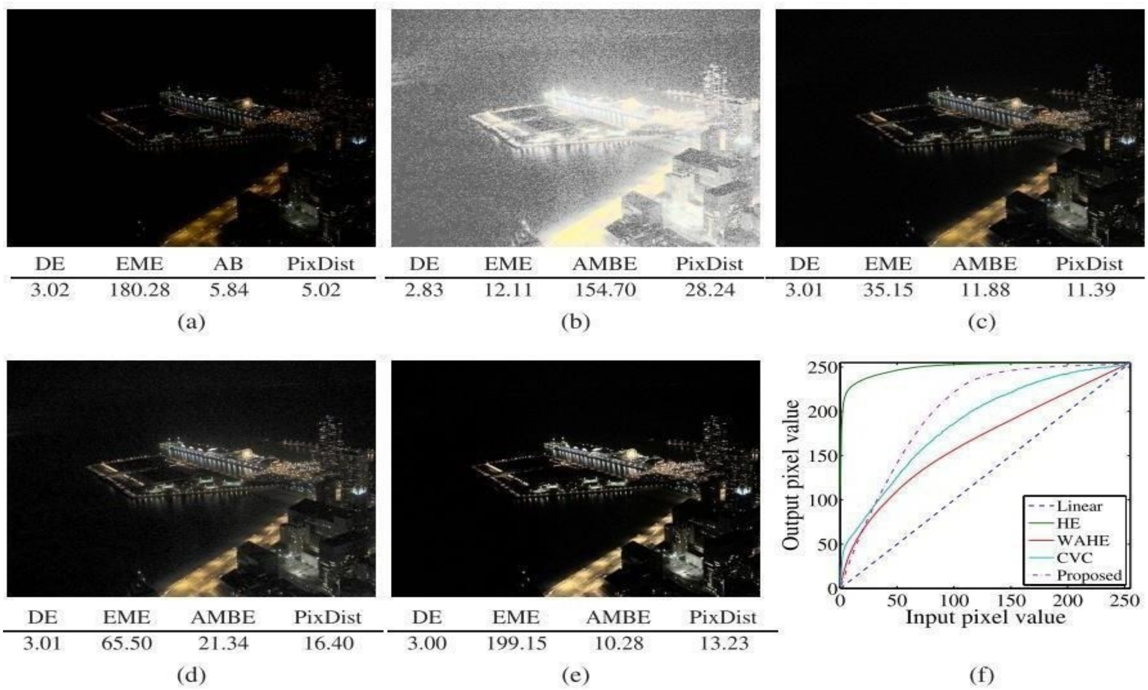


Figure. 30 CE results on the “Night View” image: (a) input image, (b) HE, (c) WAHE, (d) CVC, (e) the proposed algorithm, and (f) the comparison of the corresponding transformation functions.

Image qualities are also degraded in figure(30) when scenes are captured in very low light conditions. In the above Fig. shows a dark input image, which contains noise components. When a CE algorithm boosts gray-levels indiscriminately, it also amplifies the underlying noise components. Thus, HE yields an extremely noisy image, since it transforms the darkest gray-level to 63.

Although CVC exploits the 2D histogram information, it still experiences the over-enhancement problem due to the high histogram peak. WAHE suppresses the noise levels more effectively than HE and CVC, but it does not enhance the contrast sufficiently. On the other hand, the proposed algorithm alleviates the noise effects and clarifies the details of the buildings simultaneously. Therefore, the proposed algorithm provides the best subjective quality as well as the best EME score.

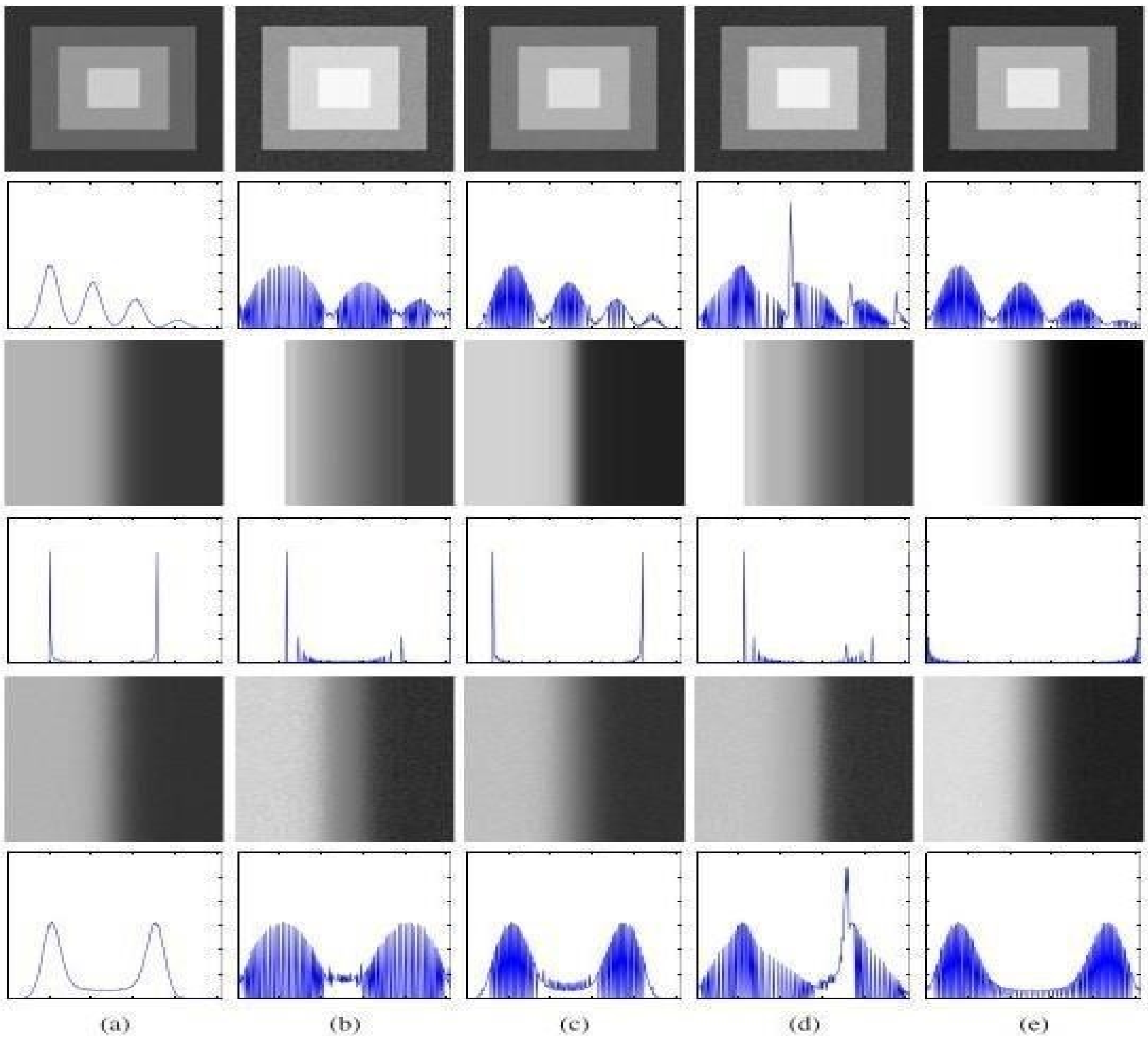


Figure. 31 CE results on three synthetic images. The first, third, and fifth rows correspond to the input and output images, and the other rows show the corresponding histograms of the upper images. (a) Input. (b) HE. (c) WAHE. (d) CVC. (e) Proposed.

B. Comparison on Synthetic Images

In above Figure(29). we compare the performances of the CE algorithms on three synthetic images. The top input image with sharp edges has the same structure as Fig 31, but it is corrupted by additive white Gaussian noise components. Therefore, we see bell shapes in the corresponding histogram. The middle input image contains a vertical gradual edge, and the bottom input image has the same edge with Gaussian noise components.

It can be observed from above Fig. that the proposed algorithm has the following advantages over the conventional algorithms: First, the proposed algorithm is robust against noise components. Whereas HE and CVC increase the noise variances and make each bell shape more widely distributed in the output histograms, the proposed algorithm preserves the bell shape with smaller magnification factors.

Therefore, the proposed algorithm preserves homogeneous regions in an image more reliably than the conventional algorithms. Second, the proposed algorithm exploits the entire dynamic range. Given the equality constraint in (11), the proposed algorithm attempts to maximize the gray-level differences of output pixels. As a result, the proposed algorithm always transforms the darkest and the brightest pixels to the minimum and the maximum gray-levels, respectively.

On the contrary, the conventional algorithms may not use the entire dynamic range, depending on the histograms of absolute gray-levels. Therefore, the proposed algorithm generally achieves higher contrast ratios than the conventional algorithms, which is confirmed by the middle and the bottom images in above Fig 31

C. Computation Complexity

TABLE 4

Analysis of the computational complexities of the ce algorithms. h and w denote the height and the width of an input image, and k is the number of gray-levels. also, w2 in cvc denotes the block size in its block-based processing.

	HE	WAHE	CVC	Proposed
A: Histogram acquisition	$\mathcal{O}(HW)$	$\mathcal{O}(HW)$	$\mathcal{O}(w^2HW)$	$\mathcal{O}(HW)$
B: Histogram modification	-	$\mathcal{O}(K)$	$\mathcal{O}(K^2)$	$\mathcal{O}(K^2)$
C: Mapping construction	$\mathcal{O}(K)$	$\mathcal{O}(K)$	$\mathcal{O}(K^3)$	$\mathcal{O}(K^2)$
Total	$\mathcal{O}(HW+K)$	$\mathcal{O}(HW+K)$	$\mathcal{O}(w^2HW+K^3)$	$\mathcal{O}(HW+K^2)$
Computation Times (ms)	7.3	17.5	7865.0	29.0

In Table (4) We analyse the computational complexities of the CE algorithms to process an image of resolution H × W with K gray-levels. We divide the whole process into 3 steps: (A) the acquisition of an input histogram, (B) the modification of the histogram, And the (C) construction of the transformation function. Table 4 compares the computational complexities and lists the average computation times over the 600 test images.

We use a personal computer with a 3.3-GHz CPU, and all algorithms are straightforwardly implemented in MATLAB without optimization. HE and WAHE require low complexities, since they modify an acquired histogram and calculate the transformation function only once. CVC demands the highest computational burden, since it solves the matrix inverse problem to obtain the desired 2D histogram.

Moreover, CVC adopts the block-based acquisition and processing of the 2D histogram information, and its complexity is proportional to the block size w2. Notice that the proposed algorithm is much simpler than CVC, although both algorithms are based on the 2D histogram information. The proposed algorithm takes only 29 ms to process an image on average.

Chapter 5

CONCLUSION

A CE algorithm is proposed to preserve the shape of the histogram by utilizing the locality condition at each intensity level, which improve the image details. The locality condition is designed to represent local structures of a stretched histogram. By locality-preserving property the local structure of the histogram is preserved after histogram processing. The performance of CE algorithms, is assessed using the subjective quality assessment for 20 test images. The results are the tested against other histogram-based methods. The proposed algorithm yields better or comparable enhanced images to that of other methods. Objective analysis is done and the results are promising

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