

# A Combinational Histogram Equalization Related to Contrast Image Enhancement

Dr. B. P. Santosh Kumar

Assistant Professor, B.Tech, M.Tech, Ph.D., MISTE,  
Department of ECE, YSR Engineering College of  
Yogi Vemana University, Proddatur, Kadapa, AP,

T. Vishnu Vardhan; Y. Naga Jagadeesh;

N.Shiva Ravi Kumar; C.Lakshmi Devi.  
B.Tech Student, Department of ECE, YSR Engineering  
College of Yogi Vemana University, Proddatur, Kadapa ,

**Abstract**—The limitation to the most commonly used histogram equalization (HE) technique is the inconsideration of the neighbourhood info near each pixel for contrast enhancement. This gives rise to noise in the output image. Image enhancement tools are often classified into point operations and spatial operations. To overcome this effect, a combinational images of histogram equalization (CHE) based technique is suggested. The focus is to utilize the information among each pixel and its neighbours, which improves the contrast of an image. This method is used in an only two-dimensional images. This histogram is using the original image and its intermediate image. Further, it does not require a target uniform distribution for generating the output. The 2-D cumulative distribution function (CDF) is utilized as a mapping function to get the output pixel intensity. The experimental analysis indicates that the procedure produces better results than the HE based contrast enhancement algorithms. More significantly, it produces the best results even for images having a narrow dynamic range. The implementation simplicity of the proposed algorithm may attract researchers to explore the idea for new applications in image processing.

**Keywords**— Images; intermediate image; histogram equalization; cumulative distribution.

## I. INTRODUCTION

Presently, high-quality digital cameras are indeed the most widely used devices to acquire images. They are extensively used in cell phones, personal digital assistants, robots, medical systems and surveillance, and home security systems. Over the years, the quality of the images acquired has significantly improved due to the development of technology. Still, there are varieties of problems that need to be addressed regarding the quality of the images. Some of the problems include contrast defects, chromatic anomalies, noise, and geometrical distortions, focus defects, etc. Many image processing techniques are reported in the literature to address such problems (Gonzalez and Woods, 2009). In this paper, we are primarily concerned with image enhancement or contrast enhancement to be more specific. Image enhancement entails the modification of an image such that the output image is either more pleasing to the human eye, or contains more information and less noise, useful for further processing. Image enhancement techniques are used either as pre-processing steps or as post processing steps to generate a visually desirable image. This includes various contrast enhancement techniques to enhance the edges of the image. Image enhancement finds application in numerous areas, for instance, medical imaging, remote sensing, television, microscopic imaging, etc.

One of the main quality impairment of a digital image is low contrast. Low contrast is caused by many factors such as uneven illumination, the addition of noise during transmission, analog to digital transformations, etc. Several algorithms for contrast enhancement are proposed in the literature. Based on the information available in the literature (Tang et al., 2003), contrast enhancement algorithms are classified into two categories: transform domain and spatial domain. The transform domain algorithms partition an input image into various sub-bands of frequency components. The image is then enhanced by modifying the magnitude of frequency components locally or globally. Such calculations are computationally complex and time-consuming. Moreover, to produce an output image free from distortions and visual artefacts, such algorithms require proper settings of the related parameters. The strategy accomplishes both global and local contrast improvement with an appropriate parameter choice.

In general, it is impossible to design a contrast enhancement method that produces a visual artefact free output. Choosing an appropriate contrast enhancement algorithm is difficult because of the absence of trustworthy and dependable measures to evaluate the quality of the output image. Moreover, enhancement algorithms generally depend on the legitimate parameter choice, which also experiences the absence of the tried and true measures.

The proposed method uses the correlation between the intensity of a pixel and the average intensity value of its neighbourhood to improve the contrast of the image. The correlation is achieved by building the histogram.

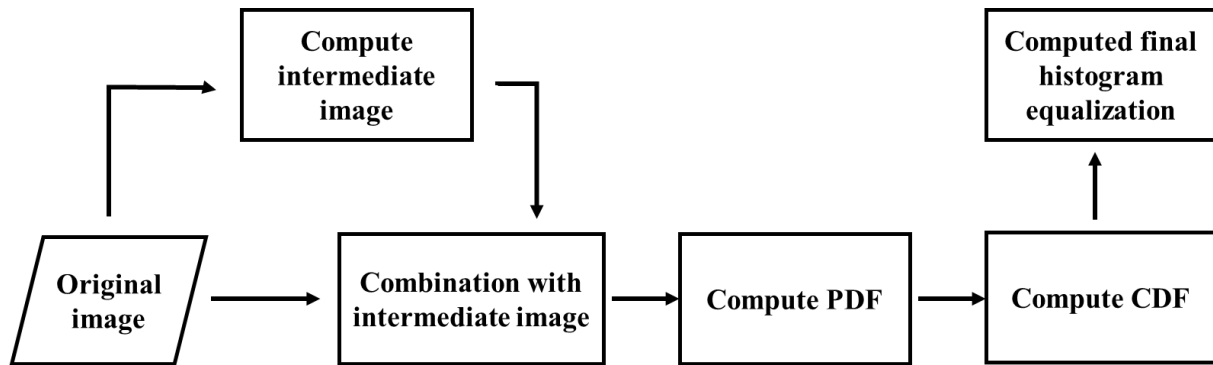


Fig 1: Schematic block diagram of the suggested technique.

A histogram is created by choosing a group of local pixel attributes and building a multidimensional histogram. The individual cells in the histogram matrix represent the number of pixels in the image expressed by a certain combination of attribute values. For instance, consider a histogram that combines the pixel intensity information of an image with the pixel neighbourhood average intensity information from another image.

A given pixel in an image has intensity levels  $\{0, L-1\}$  and its neighbourhood average intensity levels  $\{0, L-1\}$ . The histogram will contain  $L \times L$  entries. Each value corresponds to a particular pixel intensity value and its corresponding neighbourhood average intensity value at the same location. The value stored here is the number of times the intensity pair occurs in the two images. More precisely, we can develop a histogram with a given set of  $k$  attributes, where the  $i^{\text{th}}$  attribute has  $711$  possible values. A histogram is a  $k$ -dimensional matrix so that each element represents the number of pixels in an image expressed by a  $k$ -tuple of attribute values. The dimension of the histogram matrix is, therefore  $n-m$ , the number of feasible permutations of the values of each attribute.

#### A. calculating mean value of an image:

Let  $I$  represent a grey scale image of size  $M \times N$  with  $L$  intensity levels  $G = \{0, 1 \dots L-1\}$ . Let  $f(x, y)$  be the grey value of the pixel at the location  $(x, y)$  where  $x \in \{1, 2 \dots M\}$ ,  $y \in \{1, 2 \dots N\}$ . the total number of pixels is  $M \times N$ . Let  $\bar{I}$  represent the average image derived from  $I$ . The size of  $\bar{I}$  is the same as  $I$  with  $L$  intensity levels. Let  $g(x, y)$  be the grey value of the pixel at the corresponding location  $(x, y)$  in  $\bar{I}$ . The  $g(x, y)$  is computed in a  $w^2$  neighbouring window, expressed as,

$$g(x, y) = \left\lfloor \frac{1}{w \times w} \sum_{m=-k}^k \sum_{n=-k}^k f(x+m, y+n) \right\rfloor \quad (1)$$

Where  $k=w/2$ , Note that  $w < \min(M, N)$ .  $w$  is typically set as an odd value. Here, it is taken as three. However, researchers can use any other values of  $w$  for computing the average image. Now  $f(x, y)$  (from image  $I$ ) and  $g(x, y)$  (from image  $\bar{I}$ ) are taken as a feature to construct the histogram. Let  $h(i, j)$  be the count of the number of times the pair  $(i, j)$  appears, where  $f(x, y) = i$  and  $g(x, y) = j$ . Now utilizing  $(i, j)$  and  $h(i, j)$ , the histogram is formed.

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#### B. calculate the Probability Distribution Function of an image:

The conventional approach for image enhancement is to replace individual pixel intensities with the required intensity values by forming a one-dimensional (1-D) histogram of the input image. Then the required intensity values are computed from the corresponding probability distribution. The 1-D histogram equalization technique uses a discrete transformation function as defined below to generate the output pixel intensity.

$$S_v = T(r_v) = (L-1) \sum_{k=0}^v p(r_k), \quad v = 0, 1, 2, \dots, L-1 \quad (2)$$

Where  $S_v$  represents the equalized grey level in the output image,  $r_v$  is the grey level of the pixel in the input image.  $T(\bullet)$  represents the transformation operator.  $p(r_k)$  Represents the probability of occurrence of grey level  $r_k$ . It is to be noted that the probability of occurrence of grey level  $r_k$  is represented as,

$$p(r_k) = \frac{1}{MN} \sum_{k=0}^v n_k, \quad v = 0, 1, 2, \dots, L-1 \quad (3)$$

Note that this equation is not used in any of our calculations. However, it is presented here for the sake of completeness. Such an approach does not consider the information contained around each pixel while constructing the histogram. The histogram takes into account the local neighbourhood information around each pixel. In order to construct the histogram, the average intensity value around each pixel is calculated. This histogram takes into consideration the correlation existing between intensity values in a small neighbourhood of the image, which the conventional approaches ignore. The histogram is expressed as:

$$H = \{h(i, j) | 0 \leq i \leq L-1, 0 \leq j \leq L-1\}. \quad (4)$$

The term  $h(i, j)$  is the number of occurrences of the grey level pair  $f(x, y)$  and  $g(x, y)$  at the same spatial location  $(x, y)$  of the images  $I$  and  $\bar{I}$  respectively. It represents the count function. As  $i$  and  $j$  can take any possible integer value between 0 and  $L-1$ , the number of pixel pair combinations possible are  $L \times L$ . Therefore, the histogram  $H$  will contain  $L \times L$  entries.

The combined histogram for an example island image is shown in Fig. 1.

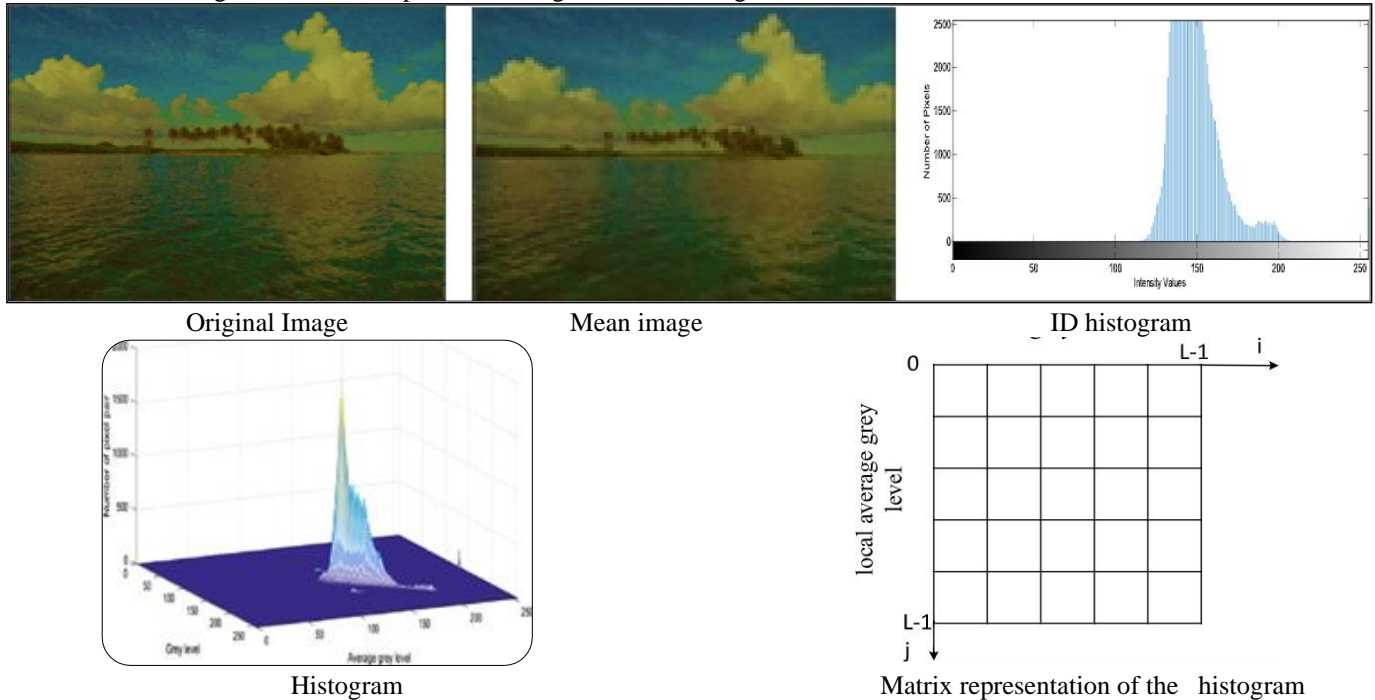


Fig 2: Representation of histogram concept.

Fig 2 represents the histogram concept. The original island image is taken. Its average image is obtained using (1). Here the window size is taken three. The ID histogram is shown for comparison. The histogram is formed using (4). The histogram is shown as a matrix. The horizontal axis #1 ( $f(x, y) = i$ ) represents the grey levels of the original image and the horizontal axis #2 ( $g(x, y) = j$ ) represents the grey levels of the average image in the 3D plot. The entries of the histogram  $h(i, j)$  (count function) show the number of times the pixel pair  $(i, j)$  appears and are represented by the vertical axis of the 3D plot.

#### C. Calculate the Cumulative Distribution Function of an image:

The two-dimensional (2D) cumulative distribution function (CDF) is obtained from the count function as given below:

$$CDF(i, j) = \sum_{m=0}^i \sum_{n=0}^j h(m, n) \quad (5)$$

Note that the computation of CDF does not depend on the size (M, N) of the images.

In this paper, we use this 2D CDF value to generate the contrast enhanced output pixel intensity. The equalized value of the intensity pairs  $(i, j)$  in the output image using the proposed method is obtained as:

$$h_{eq} = \text{round}\left(\frac{L-1}{MN-1} (CDF(i, j) - CDF(i, j)_{min})\right). \quad (6)$$

Where  $CDF(i, j)_{min}$  the minimum non-zero value of the CDF is computed using (5). Here, the size of the image (MN) appears in the denominator so that the equalized intensity levels remain within the range  $\{0 \dots L-1\}$ . The equalized histogram matrix is now represented as:

$$H_{eq} = \{h_{eq}(i, j) | 0 \leq i \leq L-1, 0 \leq j \leq L-1\}. \quad (7)$$

It is to be noted that the dynamic range of entries of the equalized histogram matrix is extended. Then the original intensity values  $f(x, y) = i$  are replaced by  $h_{eq}(i, j)$  at all the occurrences of  $i$  with  $j$  only. Note that  $f(x, y) = i$  may

have multiple occurrences in the original sub-image. Separately for each  $g(x, y) = j$ , the original values of  $f(x, y) = i$  are replaced by the equalized values. This is further explained in the example given below. It gives the enhanced image whose dynamic range is  $\{0 \dots L-1\}$ . A schematic block diagram of our suggested technique is shown in Fig 2.

## II. ALGORITHM OF THE CONTRAST HISTOGRAM EQUALISATION

The algorithm for the suggested technique consists of the following processing steps.

**Step-1:** Consider the input image  $I$  and compute the average image  $\bar{I}$  using (1) where each pixel intensity value is substituted by the average intensity value of its neighbouring pixels.

**Step-2:** Compute the histogram by comparing the input image  $I$  and the average image  $\bar{I}$  using (4).

**Step-3:** The histogram count function is then used to obtain the two-dimensional cumulative distribution function using (5).

**Step-4:** The output pixel intensity is calculated using (6) and the original intensity values  $F(x, y) = i$  are mapped to the equalized ones at all occurrences of pair  $(i, j)$  only. The final mapping produces the output image with a dynamic range that spans a wider range of grey-level scale.

To explain the proposed method, a small sub-image matrix is considered and the results are shown below in Table 1. Let an 8-bit grey scale sub-image  $I$  of size  $6 \times 6$  have intensity values as shown in Table.1 (a). The average sub-image  $\bar{I}$  obtained using (1) is shown in Table. 1 (b).

102	123	153	196	174	43
58	109	167	211	189	65
29	87	167	240	204	94
14	72	182	247	218	123
0	131	225	145	80	21
138	255	233	51	7	36

(a)

63	96	99	100	98	64
93	143	149	152	148	96
91	141	149	153	151	98
89	139	149	152	148	96
93	144	150	147	141	92
63	98	100	95	90	58

(b)

Intensity level pairs		Count	CDF	$h_{eq}(i, j)$	Intensity level pairs		Count	CDF	$h_{eq}(i, j)$
$I$	$\bar{I}$				$I$	$\bar{I}$			
112	93	1	1	0	146	144	1	19	131
122	90	1	2	7	148	63	1	20	138
130	89	1	3	14	148	147	1	21	145
132	92	1	4	21	149	99	1	22	153
133	91	1	5	29	149	149	2	24	167
134	58	1	6	36	150	98	1	25	174
135	64	1	7	43	150	149	1	26	182
136	95	1	8	51	152	148	1	27	189
137	93	1	9	58	154	100	1	28	196
139	96	1	10	65	154	151	1	29	204
140	139	1	11	72	155	152	1	30	211
140	141	1	12	80	156	148	1	31	218
141	141	1	13	87	156	150	1	32	225
142	98	1	14	94	158	100	1	33	233
143	63	1	15	102	158	153	1	34	240
143	143	1	16	109	160	152	1	35	247
145	96	2	18	123	164	98	1	36	255

(c)

102	123	153	196	174	43
58	109	167	211	189	65
29	87	167	240	204	94
14	72	182	247	218	123
0	131	225	145	80	21
138	255	233	51	7	36

(d)

Table 1: Example sub-image to demonstrate histogram equalization. (a) Sample sub image matrix, (b) Average sub image matrix, (c) histogram equalization, (d) Equalized sub image matrix.

An example cameraman grey scale image and its contrast enhanced results using different methods are presented in table 1. The cameraman image shown has bright and dark areas. The background contains a light coloured sky and building. The unequalised histogram confirms the concentration of intensity values near the origin. The output

images found with HE, MWCVMHE and FHSABP methods look similar. However, the sky and cameraman's face looks degraded. HMF method gives a better contrast with minor deformations on the sky area and somehow darkens the whole image.



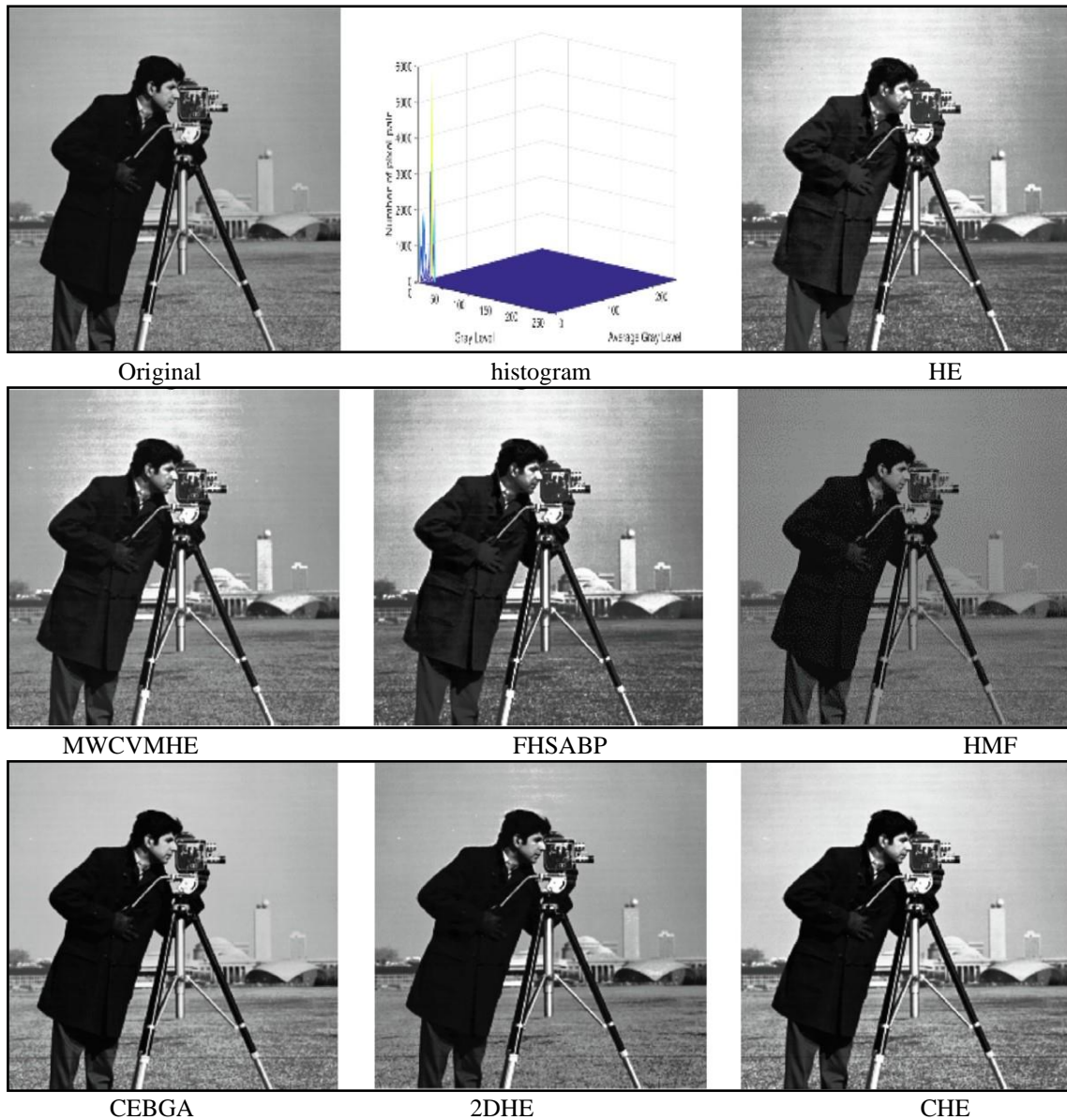


Fig 3: Results of contrast enhancement for cameraman image using different methods.

Note that the sample images used for comparison are represented as follows.

Image 1- Plane image	Image 2- Tank image	Image 3-Cameraman image	Image 4- Baboon image
Image 5-Cessna image	Image 6- Lighthouse image	Image 7_ Beach image	Image 8- Island image

The theoretical time complexity of the proposed algorithm is computed as in *Cao et al. (2018)*. The computation time required to construct the joint histogram for a 'b-bit' grey scale image of size  $M \times N$  is  $O(2MN)$ . The mapping function using two dimensional CDF requires time  $O(2^b)$ . The mapping requires  $O(MN)$  time. Hence, the total time complexity is  $O(3MN + 2^b)$ . It is to be noted that the time complexity of the proposed technique may be slightly higher than the conventional HE technique. However, it is very effective while enhancing narrow dynamic range images and reduces the noise in the enhanced image.

#### Existing parameters:

The objective measurement utilized to evaluate the performance of the approaches in preserving the original brightness of the input image is AMBE. This is expressed as

the absolute difference between the average values of the input and the output images as Wang and Ward (2007).

$$AMBE(I, O) = \frac{1}{1 + |E(I) - E(O)|} \quad (8)$$

Here,  $I$  and  $O$  represent the input and output image, respectively. Note that  $E(\cdot)$  represents the statistical mean value. A higher AMBE value shows improved brightness preservation. Discrete Entropy is a statistical quantity of randomness which is utilized to describe the textural characteristics of the input image. It determines the content in an image. A higher value indicates richer details.

It is expressed as  $DE(I) = -\sum_{k=0}^{L-1} p(r_k) * \log p(r_k)$  where  $p(r_k)$  is the probability of pixel intensity computed from the normalized histogram of the input image  $I$ . Note that  $DE(I) = -\sum_{k=0}^{L-1} p(r_k) * \log p(r_k)$  where  $p(r_k)$  the probability of pixel intensity  $r_k$  is computed from

the normalized histogram of the output image O. Then the normalized DE for the input image I and the corresponding output image O is defined as

$$DE_n = \frac{1}{1 + \frac{\log(256) - DE(O)}{\log(256) - DE(I)}} \quad (9)$$

The concept is employed to develop the suggested technique. The suggested joint histogram equalization scheme utilizes the intensity distribution surrounding each pixel in an image to improve the contrast. It is implemented for both the grey and coloured images.

Table 2  
Comparison of AMBE for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	CHE
Im	0.0260	0.0824	0.1246	0.2328	0.0330	0.3269	<b>0.3291</b>
N1	<b>0.4928</b>	0.1039	0.2140	0.0661	0.0239	0.0360	0.2639
Im	0.0944	0.1471	0.5470	0.2601	0.0782	0.0473	0.1653
N2	0.3618	0.4936	0.7338	0.0938	0.0564	0.1276	0.2487
Im	0.0197	0.2926	0.2308	0.0392	0.2225	0.5973	<b>0.6108</b>
N3	0.1141	0.7862	0.5283	0.1587	0.4376	0.0973	0.2099
Im	0.0198	0.1603	0.6743	0.0467	0.0371	0.0245	0.1712
N4	0.2495	0.5470	0.5625	0.0932	0.1524	0.1873	0.2461
Im	0.1723	0.3266	<b>0.4519</b>	0.1238	0.1301	0.1805	0.2806
N5							
Im							
N6							
Im							
N7							
Im							
N8							
Average							

Table 3  
Comparison of  $DE_n$  for different methods.

Image	HE	MWCVMHE	FHSABP	HMF	CEBGA	2DHE	CHE
Im N1	0.4920	0.4909	0.4973	0.4935	0.4975	0.4990	<b>0.5117</b>
Im N2	0.4880	0.4867	0.4895	0.4945	0.4525	0.4951	<b>0.5211</b>
Im N3	0.4458	0.4516	0.4432	0.4585	0.3876	0.4812	<b>0.4951</b>
Im N4	0.4572	0.4630	0.4588	0.4785	0.3197	0.4802	<b>0.4992</b>
Im N5	0.4623	0.4690	0.4558	0.4522	0.4560	0.4815	<b>0.4923</b>
Im N6	0.4502	0.4597	0.4538	0.4847	0.3625	0.4866	<b>0.4961</b>
Im N7	0.4528	0.4630	0.4501	0.4619	0.4389	0.4767	<b>0.4931</b>
Im N8	0.4532	0.4573	0.4517	0.4843	0.3787	0.4670	<b>0.5009</b>
Average	0.4627	0.4677	0.4625	0.4760	0.4117	0.4830	<b>0.5012</b>

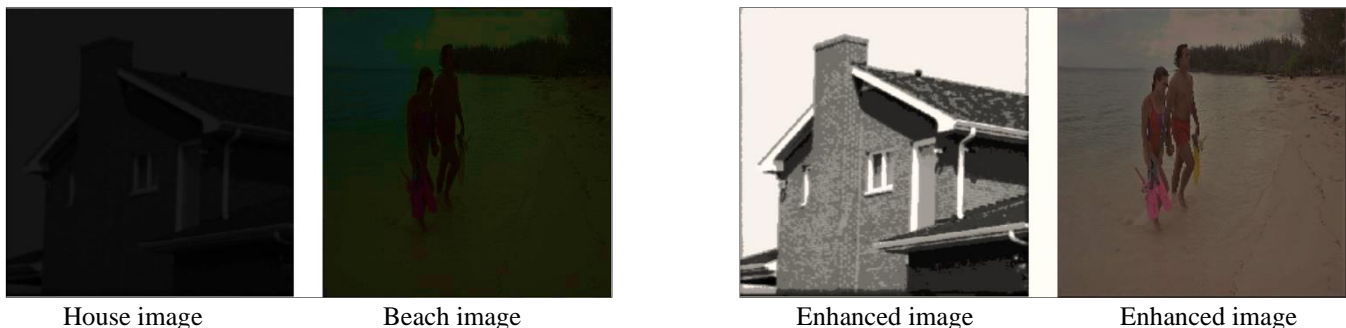


Fig. 4: Results of contrast enhancement for narrow dynamic range images using the JHE method.

### III. CONCLUSION:

In this work, a truly two dimensional (domain) concept is employed to develop the suggested technique. The suggested combinational histogram equalization

scheme utilizes the intensity distribution surrounding each pixel in an image to improve the contrast. It is implemented for both the grey and coloured images. The experimental analysis shows that the algorithm produces better or

competitive results with respect to most of the state-of-the-art algorithms. The histogram equalization produces the best results for images having a narrow dynamic range. Different quantitative assessment metrics are used to validate the algorithm.

The histogram concept used in the proposed method may pave the way for investigation of more sophisticated contrast enhancement algorithms. Further, this method can also be used along with other techniques to achieve both global and local contrast enhancement. The suggested technique is very simple but useful for contrast enhancement. It does not require a target uniform distribution and uses the CDF as the mapping function to generate the output image.

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#### ABOUT AUTHORS:



##### **Dr. B. P. Santosh Kumar**

Presently working as Assistant Professor, Department of ECE, YSR Engineering College of Yogi Vemana University, Proddatur, India. He received the B.Tech. Degree from Jawaharlal Nehru Technological University, Hyderabad, India and the M.Tech. Degree from Kerala University, Thiruvananthapuram, India. He received the Ph.D. degree from Yogi Vemana University, Kadapa, India. His current research interests include image processing.



##### **T. Vishnu Vardhan**

Presently pursuing bachelor of engineering degree in Electronics and Communication Engineering at Y.S.R.Engineering College of Yogi Vemana University proddatur, AP, India.



##### **Y. Naga Jagadeesh**

Presently pursuing bachelor of engineering degree in Electronics and Communication Engineering at Y.S.R.Engineering College of Yogi Vemana University proddatur, AP, India.



##### **N. Shiva Ravi Kumar**

Presently pursuing bachelor of engineering degree in Electronics and Communication Engineering at Y.S.R.Engineering College of Yogi Vemana University proddatur, AP, India.



##### **C. Lakshmi Devi**

Presently pursuing bachelor of engineering degree in Electronics and Communication Engineering at Y.S.R.Engineering College of Yogi Vemana University proddatur, AP, India.