Multi scale entropy based adaptive fuzzy contrast image enhancement for crowd images

Multi Scale Entropy Based Adaptive Fuzzy Contrast Image Enhancement for Crowd Images

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***Abstract*—: Contrast enhancement is a very important issue in image processing, pattern recognition and computer vision. Fuzzy logic based techniques perform enhancement using more detailed information of grayness of an image. However, these methods do not perform well on images taken in uncontrolled environment which pose different challenges such as illumination variation, perspective distortion and viewpoint variation. In this paper, we have worked to devise a more robust image enhancement method using fuzzy logic. We propose a novel multi scale entropy based measurement performed using fuzzy logic image processing and utilize it to define and enhance the contrast. For this purpose, we present a mathematical formula to calculate contrast using an adaptive amplification constant. Our approach uses both the local and global entropy information. We have experimented our algorithm on images from Crowd Counting UCF dataset, which contains very dense crowds and complex texture that stands in line with the challenges targeted in this paper. The results show an improved quality than original dataset images and prove that our method enhances the images with a more dynamic ranged contrast as well as better visual results.**

Keywords— **Defuzzification, Fuzzy domain, Grayscale, Membership Function, Multi Scale, Local Enhancement.**

I. INTRODUCTION

Image enhancement is a part of image pre-processing stage. It aims to improve information of an image. Pre-processing aims to highlight important features and suppresses irrelevant information. Image enhancement is required for many important areas such as machine vision, remote sensing, dynamic and traffic scene analysis, biomedical image analysis and autonomous navigation [1]. Image enhancement is employed to transform an image based on human visual system's characteristics. Inadequate lighting during image acquisition, or nonlinear image intensities render image interpretation to be more difficult. Hence, the object of interest, such as a dense crowd, will appear absurd. Crowd at distance from camera will have a more complex structure and weak edges, while the crowd near the camera will have high illumination exposure. In such cases, image enhancement can highlight and sharpen the object of interest in such as way that image information is not lost and the quality of the image improves.

Image enhancement techniques can be categorized as indirect or direct methods. The indirect method only stretches the intensity distribution globally, and the performance of this method for contrast enhancement is not effective in that it does not encompass information of different scales to be more information inclusive. Conversely, local methods in literature define image contrast directly using specific local measures. However, most of these methods do not accentuate the contrast of images that contain simple and complex patterns, simultaneously [2].

Images for enhancement targeted by our work are shown in Fig. 1. These images contain an interesting challenge to the state–of-the-art image enhancement techniques as these images include visual complexity of the objects under analysis; occlusion, shadowing, perspective deformation, viewpoint variance and insufficient image definition. Therefore, it is important to address the issue of image enhancement for treating the issue of perspective distortion and view invariance. An image of varying patterns, such as dense crowd near and distant from the camera, calls for local treatment to enhance image contrast and quality. The crowd-regions that are too close to the camera might need de-enhancement, while those too may require increased enhancement. Our approach performs image enhancement by means of fuzzy image processing. Fuzzy image enhancement has been used in literature for several applications of image enhancement. Fuzzy image processing incorporates even the vague areas between two classes in terms of degree of brightness or darkness. Recent techniques in fuzzy image enhancement field are discussed in detail in the next section.

Fig 1: Some of the images from UCF Crowd Dataset [3] on which Image Enhancement is performed.

We present a new contrast enhancement algorithm based on the evaluation of the contextual information. The proposed method uses adaptive power law measures for keeping the contrast stretched for better image information protection and enhancement. Most of the developed contrast enhancement techniques do not consider image dataset which include view invariance. The UCF crowd dataset [3] includes images that are captured at different camera viewpoints; images are captured at different levels of viewing sphere. Since our method uses multi scale entropy based information per patch, this attends to the issue of non-similar pattern across the image. To incorporate the local information, a crowd distance measure is introduced to estimate crowd distance from the camera. Finally, enhanced image is obtained by a new intensity transfer function, which depends on entropy difference of the patches at different scales. The long-term aim is to enhance images for better crowd estimation and localization. The exhaustive experimentation shows that the proposed algorithm results in a natural visual enhancement for dense crowd images.

This paper is organized as follows. Section II provides literature review. This section also briefly describes fuzzy image processing theory. Section III introduces the concept of multi scaled based entropy analysis to use local level information for image enhancement. This section further defines different variables and the reasoning behind every important step. In Section IV, we present results quantitative and qualitative analysis. The visual and tabulated results are discussed in detail. Section V concludes our paper with the objective achieved in this paper and future work.

II. Literature Review

The commonly used techniques for contrast enhancement fall into two categories: indirect methods of contrast enhancement and direct methods of contrast enhancement. Contrast can be measured globally and locally. The direct method provided better performance than the indirect method [4-6]. It is more appropriate to define a local contrast when an image contains non-uniform textural information.

A. Image Enhancement Methods

Image enhancement can be classified into two groups namely frequency domain and spatial domain. Enhancement In the frequency domain is conducted by mapping an image to its frequency domain and then modifying it [7, 8]. However, this method is time consuming process even with fast transformation techniques and hence makes it unsuitable for real time applications [9]. In spatial domain, pixel values in the image are directly modified for getting image enhancement. For preserving fine image textures, especially to cater for varying illumination and structures in an image, some recent works target to enhance edges [10, 11] or use color information at arbitrary scales to enhance images [12]. These methods basically share the same goal of smoothing fine-scale details without degrading image structures, although they are not explicitly designed to deal with fine complex texture,or low resolution images.. Another technique uses an alteration to gamma correction technique , where the weighted histogram of the image is used to adaptively compute gamma [13]. The algorithm requires hindsight tuning of parameters, a similar limitation to the work of [11], which affects automation and robustness of the enhancement method for complex images.

A very popular technique for image enhancement is histogram equalization (HE). The simplicity and suitable performance makes this method a commonly employed image enhancement technique which can be applied on a variety of images. Histogram Equalization distributes the intensities effectively spreading out the most frequent intensity values and stretching the dynamic range of gray values in an image [14]**.** However, HE based techniques tend to result in a washed-out enhanced image or increasing vagueness in edge information due to gray levels suppression [15]. Modified HE techniques include bi-histogram equalization [16], quadrant dynamic histogram equalization [17], brightness preserving dynamic histogram equalization [18] and Fuzzy clipped contrast-limited adaptive histogram [19]. Most of the methods discussed so far mostly use global enhancement. Global enhancement ignores local characteristics of a pixel and in some cases results in visual artifacts. Some methods use both global and local contrast enhancement [20]. The histogram is modified using a sigmoid function for global enhancement and used DCT for local contrast enhancement. In the local histogram equalization (LHE) [21], a small neighborhood region is considered for histogram equalization. LHE incorporates local property, but may introduce the checkerboard artifacts. An approach also includes spatial entropy-based contrast enhancement in discrete cosine transform (SECEDCT) [22] or bitwise manipulation [23]. The spatial entropy of a 2-D histogram is used to enhance contrast locally, while global contrast enhancement is achieved by DCT. While this method enhances images, but it is computation-costly. These techniques use crisp histograms for enhancement of digital images and suffers from intrinsic limitation of excluding the imprecision of gray values. Since gray level values in pixels are imprecise, many authors suggest fuzzy based methods to deal with intensity inexactness.

B. Fuzzy Image Processing Theory

Fuzzy image enhancement is gray level mapping into membership function which can better represent image information, and hence can be manipulated suitably for better contrast in the resulting image. Main steps in fuzzy image processing are Fuzzification, Inference Engine, Defuzzification. Fuzzification is assignment of required membership function to map images from pixel plane to fuzzy plane. Gray level range of image pixel value (0-255) is transformed to [0,1] to represents the fuzziness of pixels. In the fuzzy plane, with the help of enhancement or transformation operator, images are modified to get desired results. The choice of membership function depends on application type. This plane is also known as the inference plane. The aim is to generate an image of higher contrast than the original image in such a way that the gray levels that are closer to the mean gray level of the image has a higher weight. Fig 2 shows the general structure of fuzzy image processing.

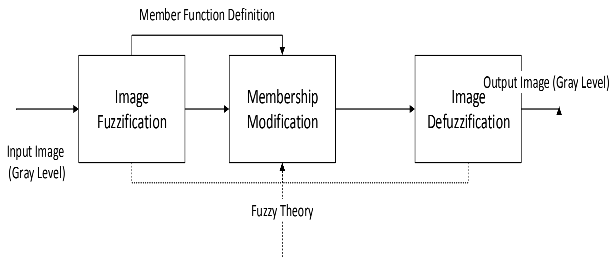

Fig 2: General fuzzy image processing structure

In the image enhancement field, fuzzy set theory has been widely utilized by many researchers [9, 24-27]. Most commonly used methods are intensity based operator (INT) which use a non-linear manner to increase or decrease the contrast. Using fuzzy methods in some cases does not perform as desired and in these cases, intuitionistic and type II fuzzy set theories are used to cater for uncertainty. Various enhancement techniques propose image enhancement techniques that optimize the information contained in the image such as optimizing entropy [28], index of fuzziness [29] and intuitionistic fuzzy [24, 30]. Another approach proposes optimization of an objective measure, exposure, which will enhance the amount of lighting exposure of the image [31]. They divided image into underexposed and overexposed regions based on this objective measure. Exposure involved different measures; entropy, contrast and visual factor of the image. Minimizing this objective measure successfully resulted in enhancement of an image. However, this method requires repetitive procedure to improve image quality and hence is computationally expensive. Only a few studies address the issue of non-uniform lighting in an image in the context of image enhancement [31, 32]. Local enhancement using fuzzy techniques has been attempted successfully to increase image details in [33-36]. However, besides local improvements, noises and artefacts are enhanced.

Since the UCF crowd dataset [3] includes images with multiplex elements in the background, and varying crowd sizes in the foreground, these methods do not perform well. This is because these methods assume uniform pattern across the test images. This assumption does not hold true for outdoor dense crowd images. Realizing these limitations, a new contrast enhancement technique needs to be developed to improve the contrast of the UCF crowd dataset images by considering different challenges of the dense crowd images. An enhancement technique needs to be explored that preserves image details and enhances crowd region in the images while keeping the background information intact.

III. Proposed Method

In this section, we address how local entropy information of the image can be used to solve over-enhanced and under-enhanced image regions. A higher entropy indicates the presence of higher details in the image [37]. In literature, the amplification constant has not been integrated with the multiscale fuzzy entropy information. This suggests that local multi scale entropy difference (MSED) has not been manipulated for image enhancement. MSED systematically examines the crowd images at different depths and finds the depth at which maximum crowd information is present. Therefore, in this paper we propose a method that will find an adaptive amplification constant which fuses MSED information with contrast amplification constant. The main purpose of this method is to enhance the contrast in fuzzy domain effectively and adaptively. The steps include mapping an image from space domain to fuzzy domain using the S-function as the membership function, defined in process A and its detailed description is presented in Method A. In Process B, we propose a more powerful and adaptive fuzzy contrast enhancement method, described in Method B, which maximizes the fuzzy measures contained in the image by using power-law transformation. Finally, in Process C, defuzzification is defined which is used to transform the gray scale image from modified fuzzy domain back to spatial domain. Process C is presented in detail in Method C.

A. *Image representation in fuzzy set notation with optimum entropy information*

An image X of size $M \times N$ with gray levels ranging from L_{min} to L_{max} can be modeled as an array of fuzzy singletons. Each element in the array is the membership value representing the degree of brightness of the gray level x where $x = L_{min}, L_{min+1}, \dots, L_{max}$. In the fuzzy set notation, we can present an image as done in literature [38]

$$X = \mathrm{U}\{\mu(m_{i,j})\} = \left\{ \frac{\mu_{i,j}}{m_{i,j}}\ i = 1,2..M, j = 1,2,..N \right\} \quad (1)$$

where $\mu(m_{i,j})$ denotes the degree of brightness intensity $m_{i,j}$ of the (i,j) pixel. The shape of S-function is commonly used for the representation of the degree of brightness of gray levels in an image [39]. It is given as

$$\mu(x_{m,n}) = \begin{cases} 0 & 0 \le X_{m,n} \le a, \\ \frac{(X_{i,j}-a)^2}{(b-a)(c-a)} & a \le X_{i,j} \le b, \\ \frac{(X_{i,j}-c)^2}{(c-b)(c-a)} & b \le X_{i,j} \le c, \\ 1 & X_{i,j} \ge c. \end{cases} \quad (2)$$

where $x_{m,n}$ is the gray level of the image X at pixel m, n and a, b and c are parameters that determined the shape of the S-function. These parameters are based on the image characteristics to map the image completely from space domain to fuzzy domain so that the membership function can retain the maximum information contained in the image. Parameter *b* is not necessarily the midpoint; it can be anywhere between the range [*a*, *c*] based on the image based suitable point. Therefore, as used by Cheng *et al.* [4], parameters *a*, *b* and *c* are calculated from image X in such a way that entropy loss is only permitted over a short range while an optimal value for *b* is found.

Fuzzy Entropy can be calculated as Paul and Majumdar [40]:

$$\begin{aligned} \mathrm{S}[\mu(x_{m,n}), \mathrm{a}, \mathrm{b}, \mathrm{c}] = &-\mu(x_{m,n})\log_2\mu(x_{m,n}) \\ &-[1-\mu(x_{m,n})]\ \log_2[1-\mu(x_{m,n})], \end{aligned} \quad (3)$$

The calculated membership function *S* transforms the image intensity levels from the spatial domain to fuzzy domain. Assume the image has gray levels from L_{min} to L_{max} Calculate the Fuzzification parameters with the technique of [4], which for the purpose of continuity and clarity is shown in Method A. The main function of Method A, as argued in [4] is to separate gray levels that may correspond to the background and the ones that may relate to noise. The information between these gray values is where the important image information is expected to lie in the range $[B_1\ B_2]$ and p_{x_m} is the mth peak of grey values. The value of b_{opt} is found where the function *S* has maximum entropy. For more details of Method A, the reader is directed to [4].

Method A: ***Optimal Fuzzification Parameters***

1. Divide the image into $J \times K$ blocks,
2. Obtain the histogram *Hist*($X_{J \times K}$) within each block.
3. Find the local maxima of the histogram, Max(*Hist*(X_1)), Max(*Hist* (X_2)),.., Max(*Hist*($X_{J \times K}$)).
4. Calculate the average height of the local maxima.
5. $\overline{Hist_{max}}(X) = \frac{1}{k}\sum_{i=1}^{k} Hist_{max}(X_i)$
6. Find the peaks whose values are more than the average height $\overline{Hist_{max}(X)}$ and save the first peak as P.
7. To determine the value of parameter a and c, we follow the method of [41]:
8. $a = (1 - f1)(\mathrm{p}_{x_1} - L\mathrm{min}) + L\mathrm{min},$
9. $if\ (a > B_1)\ then\ a = B_1$
10. $c = f2(L\mathrm{max} - \mathrm{p}_{x_n}) + \mathrm{p}_{x_n},$
11. For c, $if\ (c > B_2)\ then\ c = B_2,$
    Where low limit, B_1 and high limit, B_2 are found using entropy loss limited to values f_1 and f_2, whose values range from 0.001 to 0.005 [41]. This helps in eliminating background and noise information while keeping valuable information region. The range $[B_1\ B_2]$ can be found as:
    i. $Ent(\sum_{i=L_{min}}^{B_1} His(X)) = f_1$, and
    ii. $Ent(\sum_{i=B_2}^{L_{max}} His(X)) = f_2$,
12. Determine parameters b_{opt} such that the function S(a,b,c) has maximum entropy with the new value of b, where b ∈ [a c].
13. New S function is $\mathrm{S}(\mathrm{a}, \mathrm{b}_{opt}, \mathrm{c})$.

B. *Modification of the membership function using Contrast Enhancement with multi-scale Entropy information*

In literature, the perspective distortion has not been addressed using variable local information in the image. In case of a dense crowd image, the regions that are too close to the camera might need de-enhancement, while regions that are too far might need more enhancement keeping the contrast stretched for better information representation. In this paper, we propose a mathematical formula to calculate local information difference at different scales for image enhancement using an adaptive amplification constant which fuses local entropy difference information. Suppose an image X, with L different gray levels which are fuzzified using $\mu(x_{m,n}) = \mathrm{S}(\mathrm{a}, \mathrm{b}', \mathrm{c})$. We propose an adaptive amplification constant $\lambda_{m,n}$ that can be calculated using our proposed Method B1. The main function of Method B1 is to analyse image patches in different depths using DoG pyramids, and use the measure ρ_{diff} to calculate the new amplification constant. Variable ρ_{diff} contains the measure of pyramidal information variation at an image region.

Method B1: ***Fuzzy Amplification Constant***

1. Obtain fuzzified values of image using the parameters $a, b', c => \mu(a, b', c)$.
2. Divide Image into J x K blocks, and save the block pyramid to level s using Difference of Gaussian (DoG).
3. Formulate a matrix M representing entropy values at each scale and region R in the image, as follows
4. Matrix $M = [R_{j\times k_i}]_{J\times K}$ is represented as the following where $R_{j\times k_{si}}$ represents the entropy of image block at $j \times k$ at si scale
5. $M = \begin{bmatrix} R_{1_{s1}} & R_{1_{s2}} & \cdots & R_{1_{si}} & \cdots & R_{1_{sn}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{j\times k_{s1}} & R_{j\times k_{s2}} & \cdots & R_{j\times k_{si}} & \cdots & R_{j\times k_{sn}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{J\times K_{s1}} & R_{J\times K_{s2}} & \cdots & R_{J\times K_{si}} & \cdots & R_{J\times K_{sn}} \end{bmatrix}$
6. Find differences of entropy, D ,among the different scales. In this paper we analyze crowd patches at $n = 3$ scales:
7. $D = \left\{R_{l_{sp}} - R_{l_{sq}}\right\}$, where $l \in [1, .., J \times K]$ and $sp, sq \in [1, .., 3]$. Our analysis of set D shows that for region with crowd closer to the camera, $D_{JK_{k1,kn}}$ is mostly near or below zero. This suggests that when camera is near crowd, $D_{JK_{k1,kn}} \approx 0$. The faces near the camera appear very bright and occupy a larger area in the blocks, hence the entropy difference at different scales is not very high for this case.
8. Calculate the standard deviation of the entropy differences $D_{JK_{k1,kn}}$ and choose the scale for processing the corresponding region. The threshold of fuzzified values can be found by $Th = avg\left(D_{JK_{k1,kn}}\right) \ \forall\ D > 0$, where avg is the average operator.
9. Note the minimum and maximum value of set D and denote as $\rho_{\mathrm{min}} = D_{JK_{k1,kn+1/2}}$, and $\rho_{\mathrm{max}} = D_{JK_{k1,kn}}$
10. Compute the fuzzy entropy $\rho_{m,n}$ in each region at scale s where the difference of entropy is highest. The scale with a higher entropy difference shall contain higher information content.
11. To find the amplification constant $\lambda_{m,n}$ for each pixel (m, n) amplification constant can be computed as
12. $\lambda_{m,n} =$
$$\begin{cases} \frac{\mu(x_{m,n})}{\mathrm{p}x_l} + \left(\sigma_{min} + \beta(1 - \sigma_{min})\frac{1}{\rho_{diff}}\right) & if\ \rho_{diff} < 0 \\ \sigma_{min} + \beta(1 - \sigma_{\mathrm{min}})\left(\rho_{diff}\right) & if\ 0 \le \rho_{diff} \le Th \\ \alpha \times \left(\sigma_{min} + \beta(1 - \sigma_{\mathrm{min}})\left(\rho_{diff}\right)\right) & if\ \rho_{diff} \ge Th \end{cases}$$

where variable ρ_{diff} is calculated at all image regions and it is the entropy difference with highest standard deviation. The equation of $\lambda_{m,n}$ uses ρ_{diff} to regularize image enhancement based on region based information. The value $\frac{\mu(x_{m,n})}{\mathrm{p}x_l}$ regularizes the fuzzy values w.r.t. minimum image values, i.e.

lowest peaks, whereas σ_{min} and $1-\sigma_{min}$ represent background and foreground values, respectively. The equation is conditioned with variable ρ_{diff} whose negative value shows low degree contrast enhancement, and value below threshold means high contrast enhancement**.** The normalizing parameter β is found as $\beta = (\rho_{m,n} - \rho_{min})/(\rho_{max} - \rho_{min})$ and the value for α is found as follows

$$\alpha = \begin{cases} 1 & if\ \mathrm{p}_{x_{th}} \leq \mu_{(x_{m,n})} < \mathrm{p}_{x_h} \\ \frac{\mu_{(x_{m,n})}}{\mathrm{p}_{x_h}} & if\ \mu_{(x_{m,n})} \geq \mathrm{p}_{x_h} \end{cases} \quad (4)$$

where σ_{min} is the standard deviation of the fuzzified image, $\mu_{(x_{m,n})}$ and p_{x_h} is the highest image peak to regularize image values as described in Method A earlier. This amplification constant proposed in this paper is used to describe new image contrast.

The contrast of the image can be found using different methods such as Root Mean Square (RMS) [42]**,** Michelson contrast or Weber method [43]. As described in [41, 44], Method B2 outlines how new contrast of the image shall be calculated using the output form method B1. Method B2 is followed close as that in [44].

Method B2: ***Calculating Modified Contrast and New Membership Value***

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1. Extract gradient edge information in each $J\ x\ K$ block using Laplace of Gaussian (LoG) or Sobel operator. Selection of the edge operator is based on the application and nature of the image. For our application, Sobel operator was used to find edge value of the image in fuzzy domain $\delta_{\mu(xmn)}$. Mean edge value, $\overline{\overline{\mathrm{E}}}$, can be calculated using a moving window, $W_{m,n}$, using the formula:
2. $\overline{\mathrm{E}}\,(\mu_{x_{mn}}) = \frac{\sum_{m,n\,\epsilon\, W_{m,n}} \delta_{\mu(x_{mn})} \times \mu_{x_{mn}}}{\sum \delta_{\mu(x_{mn})}}$
3. Evaluate the RMS contrast, C, related to the membership value $\mu_{x_{mn}}$ using the following formula
4. $C = \sqrt{\frac{1}{nm} \sum_{i=0}^{n-1} \sum_{j=0}^{m-1} (\mu_{W_{mn}} - \overline{E(}\mu_{x_{mn}}))^2}$
5. Based on our amplification constant, $\lambda_{m,n}$, calculate modified contrast value:
6. The new contrast is $C'_{m,n} = (C_{m,n})^{\lambda_{m,n}}$
7. Finally calculate modified membership value μ'_{mn} as:

$$\mu'_{mn} = \begin{cases} \bar{E}_{mn} \times \frac{(1 - C'_{mn})}{(1 + C'_{mn})} & if\ \mu_{mn} \leq E_{mn} \\ \bar{E}_{mn} \times \frac{(1 + C'_{mn})}{(1 - C'_{mn})} & if\ \mu_{mn} > E_{mn} \end{cases}$$

C. *Defuzzification of Membership value to Gray Levels*

Now that the contrast of fuzzified image has been modified, the image must be transformed back to gray level values. The transformation of the enhanced fuzzified image, μ'_X, can be done using the method proposed by Cheng *et al.* [41] for S function based enhancements:

$$L'_{m,n} = \begin{cases} L_{m,n} & if\ \mu_{mn} = 0 \\ L_{min} + \frac{(L_{max} - L_{min})\left(\mu_{mn}\,(b-a)(c-a)\right)^{0.5}}{c-a} & if\ 0 < \mu_{mn} < \frac{b-a}{c-a} \\ L_{min} + \frac{(L_{max} - L_{min})\left((1-\mu_{mn}')\,(c-b)(c-a)\right)^{0.5}}{c-a} & if\ \frac{b-a}{c-a} < \mu_{mn} < 1 \\ L_{m,n} & if\ \mu_{mn} = 1 \end{cases} \quad (5)$$

where $L'_{m,n}$ in equation 5 holds the enhanced image after modification and defuzzification stage. The results of defuzzification differ from that of [41] because of our proposed method of contrast enhancement.

IV. Experiment and Discussion

The experimental results from the UCF Crowd database [3] is presented in this section. We demonstrated the performance of the developed algorithm compared with other existing fuzzy and non-fuzzy gray-scale enhancement techniques. It must be noted that the nature of database used for enhancement is of special nature and hence a need for a novel approach for image enhancement has been addressed in our work. As we mentioned earlier, the indirect image enhancement methods only stretch the intensity distribution globally or the performance of local method for contrast enhancement is not effective. The images from this dataset contain perspective distortion and viewpoint invariance as well as many underexposed and overexposed regions. Hence, these images are used for enhancement test analysis.

In order to demonstrate the performance of the proposed method, we compared qualitatively and quantitatively the experimental results of the proposed approach with other state of the art methods namely Histogram Equalization, Local Laplacian Filters (LLF) [11], Multilevel fuzzy Enhancement (FGMT) [1] and Edge-aware Filters [12] . The enhanced image is analyzed in terms of its qualitative and quantitative analysis such as Contrast Improvement Index (CII), Quality Index (QI), Entropy, Luminance Distortion (LD), Gradient Average and other measures suggested in a recent study for contrast enhancement validation [45]. The proposed method has been implemented on Intel Core i5 CPU 2GHz using Matlab R2013b.

A. *Qualitative evaluation*

In our method, each block of the image is studied at different levels and enhanced as per the information contained in the block. To clarify the enhancement result proposed by our technique, in this section we present a visual comparison of different techniques with ours. Fig 3 shows the original image (Fig 3(a)). The result of the well-known Histogram Equalization. FGMT method [46] and our proposed method is shown in Fig. 3(b), 3(c) and 3(d) respectively.

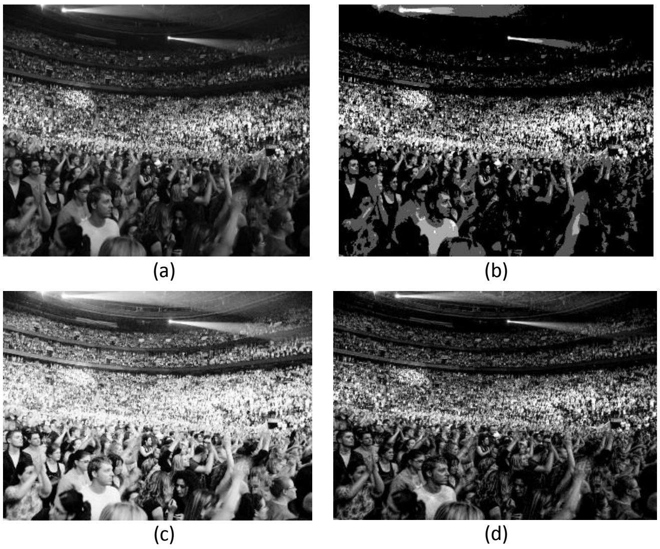


Fig 3 (a) original image in UCF Crowd dataset, (b) enhanced image using Histogram Equalization (c) result using method in [46] (d) enhancement result using our proposed method

The dynamic range histogram of Fig. 3 are shown in Fig 4(a), Fig 4(b), Fig 4(c) and Fig 4(d), subsequently. The result of Histogram Equalization is over-enhanced and the details of the image are not clear, as shown in Fig 3(b). Likewise, the analysis of the dynamic range of HE results shows that the gray values get compressed and hence the loss of features of the image occurs. Fig 4(d) illustrates that our proposed method enhances contrast in a more dynamic way; the contrast is evenly spread and the gray values are not skipped or clustered, unlike the result in 4(b).

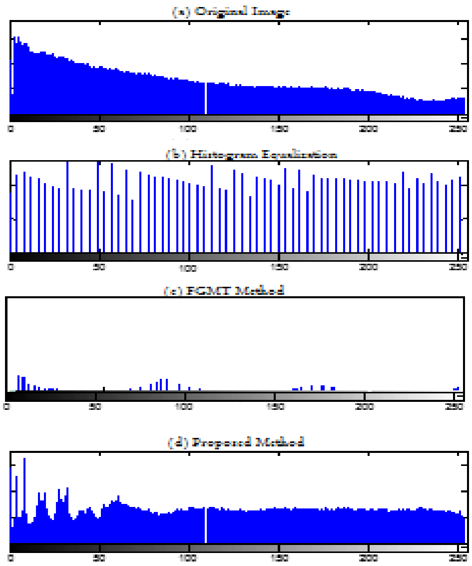


Fig 4 The histogram of an original image from UCF Crowd dataset [3] is shown in 4(a). The effect on the dynamic range after it was enhanced using Histogram Equalization 4(b). The result of FGMT technique [46] shows a poor contrast of the image. This also hints to why locating the crowd heads and distinguishing objects in image from humans becomes more difficult. Dynamic range of the image after enhancement using our proposed method is shown in Fig 4(d)

To further illustrate and compare our results, Fig 5 shows some of the original images from the UCF Crowd dataset [3] and the result of enhancement with different methods. The results of the proposed method in Fig 5(e), first row show that the proposed methods resulted in crowd head positions being more sharp. Also, in the shadow region, the proposed method enhances the crowd heads. Second row of Fig 5(e) clarifies how the crowd in the depth is also easy to localize. The results of Edge-aware Filters [12] in 5(c) displays the distant crowd as smudged and the crispness of facial features is reduced. This compromises the objective we wish to achieve. As shown in Fig 5(d), the LLF[11] technique results in overexposure of the crowd close to camera while that in the distant has a noise like effect as a result of enhancement. However, in some images, such as shown in Fig 5(d) third row, the details distant from the camera are well enhanced. The visual analysis presented in the Fig 3 to 5 is supported by quantitative analysis in the next sub-section.

B. Quantitative analysis

In addition to the visual analysis, statistical accuracy measures are analyzed for better comparison among the proposed and state-of-the-art methods. These measures are Absolute Mean Brightness Error (AMBE), Luminance Distortion (LD), Peak Signal to Noise Ratio (PSNR), Contrast Improvement Index (CII) and entropy. These image quality measures are chosen for their popularity and recommendation in literature for image quality analysis [36, 45].

LD considers the correlation of mean luminance between the enhanced and the original images and is in the range [0 1]. The mean luminance of the enhanced image is almost similar to the original image if the LD approaches 1. This value suggests that $\bar{X} \approx \bar{Y}$, the brightness is preserved as $\bar{X}$ and $\bar{Y}$ are gray values for original and modified images. LD can be found using

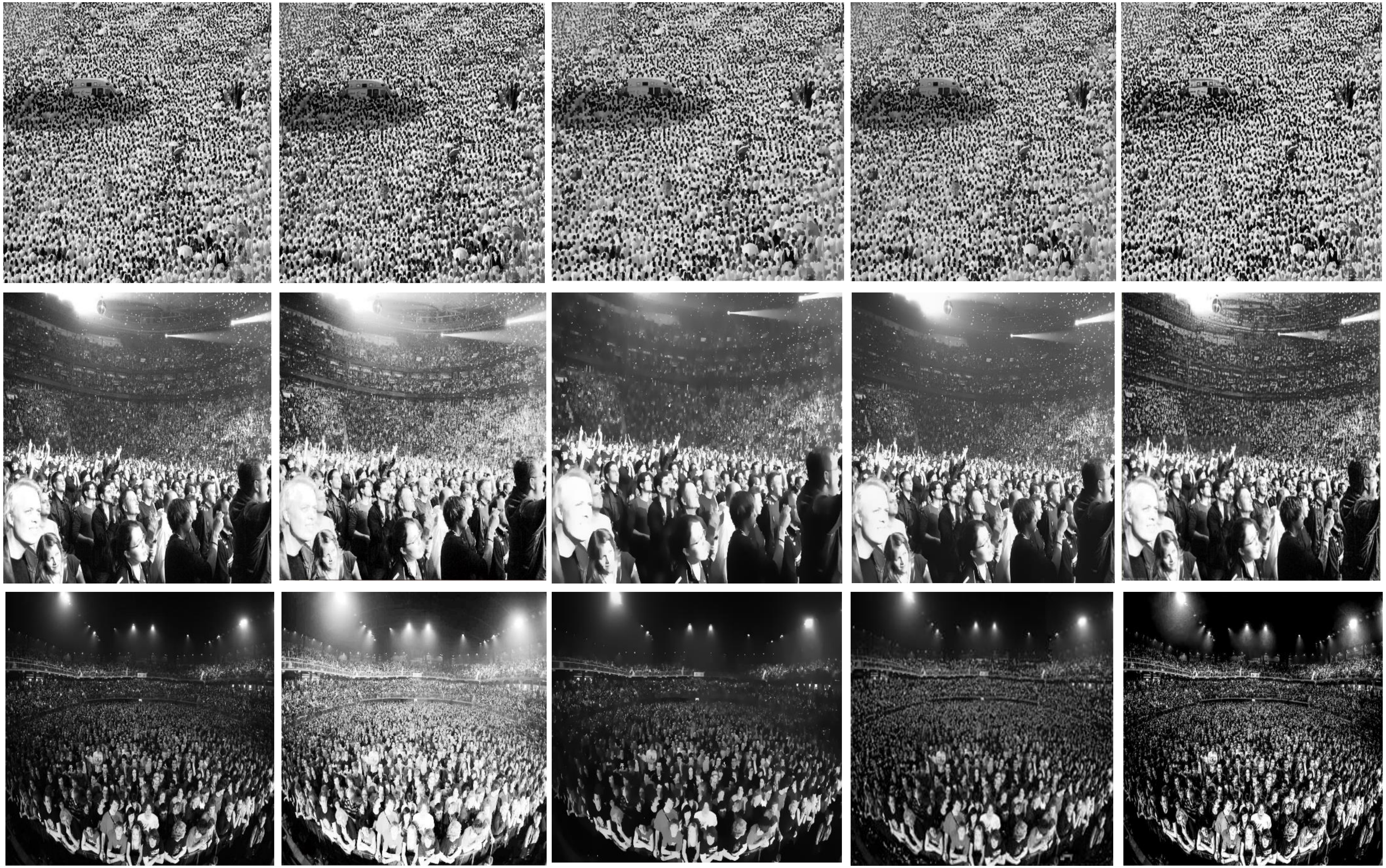
$$LD = \frac{2(\bar{X} \text{ x } \bar{Y})}{\bar{X}^2 + \bar{Y}^2} \tag{6}$$

Since the details of the image also need to be maintained, so the entropy is used to measure the capability of detail preservation. Similarly, the PSNR must not decrease from that in original image. a higher PSNR value shows absence of noise and over-enhancement. Contrast Improvement Index (CII) defined as:

$$\text{CII} = \frac{C_{Proposed}}{C_{Original}} \tag{7}$$

where $C_{Proposed}$ and $C_{Original}$ are the average values of the local contrast in the output and original images, respectively. The greater value of CII indicates that the given image quality is better. Similarly the measure of quality index (QI) [47] can be found as

$$QI = \frac{4\,\sigma_{xy}\,\overline{x}\,\overline{y}}{(\sigma_x^2+\sigma_y^2)[(\bar{x}^2)+(\bar{y}^2)]} \tag{8}$$



(a) (b) (c) (d) (e)

Figure 5: Comparison of enhancement results for some crowd images from the dataset are shown in a, b, c d and e: Original images are shown in 5(a). Enhanced image result using state-of-the-art technique Histogram Equalization (HE) [48] is shown in 5(b) . Crowd image enhancement result by [12] and [11] are shown in 5(c) and 5(d), respectively. The result of our proposed enhancement technique is presented in 5(e). Row 1 of 5(e) illustrates the effect of shadow minimized and the crowd can be more clearly seen. Row 2 (5e) shows how our result enhanced the region where the dense crowd is sitting at a higher aisle. Other methods either result in very high brightness (5b) or blurring of the dense crowds in higher aisles. Row 3 (5e) shows how the result enhances crowd regions in very deep field of view, whereas other methods overexpose (5b) or underexpose the crowd in far distance (5c).

Table 1 Exposure Level comparison of different levels from 10 random images of UCF-CC Dataset

Test Image	Methods											
	Original		*Histogram Equalization[48]*		*FGMT [46]*		*Edge-aware Filters [12]*		*LLF [11]*		*Proposed*	
	Average Gradient	*Entropy*	*Average Gradient*	*Entropy*	*Average Gradient*	*Entropy*	*Average Gradient*	*Entropy*	*Average Gradient*	*Entropy*	*Average Gradient*	*Entropy*
1	18.10	7.86	18.59	5.99	14.75	7.81	13.97	7.82	11.24	7.59	**18.79**	**7.86**
2	24.81	7.94	**26.12**	5.99	17.83	6.10	19.35	7.86	14.14	7.91	25.64	**7.94**
3	18.51	7.74	**23.40**	5.98	19.20	7.81	12.90	7.60	10.41	7.81	19.72	**7.80**
4	9.53	7.62	11.02	5.95	9.63	7.82	5.65	7.53	8.12	7.45	**11.16**	**7.64**
5	9.57	7.33	**12.54**	5.92	7.14	7.24	6.32	7.28	7.45	6.95	10.50	**7.31**
6	8.57	7.05	**13.64**	5.93	6.04	6.96	5.00	6.89	7.17	6.73	9.26	**7.03**
7	12.25	7.53	13.55	5.95	11.09	**7.51**	8.41	7.49	9.11	7.16	**13.65**	7.42
8	17.04	7.84	**20.69**	5.99	18.15	7.89	11.46	7.73	10.17	**7.84**	19.39	7.83
9	17.31	7.80	22.66	5.98	19.98	7.91	11.71	7.67	11.58	7.83	**22.81**	**7.82**
10	22.35	7.76	**23.80**	5.95	23.13	7.78	16.67	7.71	12.30	7.68	23.18	**7.78**

In equation 8, x, y are average values of compared images and σ represents the standard deviation among the two measures. Fig 6 shows CII and QI comparisons of the proposed method and that of Histogram Equalization of the randomly selected images previously analyses in Table 1. CII and QI indexes of the proposed method are higher than those of HE. This represents that the enhanced image has improved image contrast and quality.

The results obtained for enhancement of UCF dataset [3] are catalogued in Table 1. Our proposed method, in most images, enhances the crowd regions which are distant to the camera and less illuminated. Table 1 shows average gradient and entropy information of the 10 random images from UCF dataset. A higher average gradient of an image signifies that the enhanced image contains more gray levels and a higher image definition [49]. A higher Entropy suggests the enhanced image contains more information. To analyse how image information is preserved and how the gradient is improved, refer to Table 1. The values in bold show which images improved the average gradient to highest. The bold entropy values show the closest

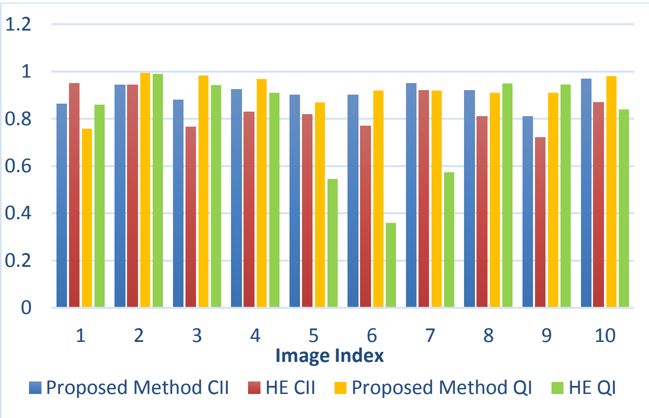


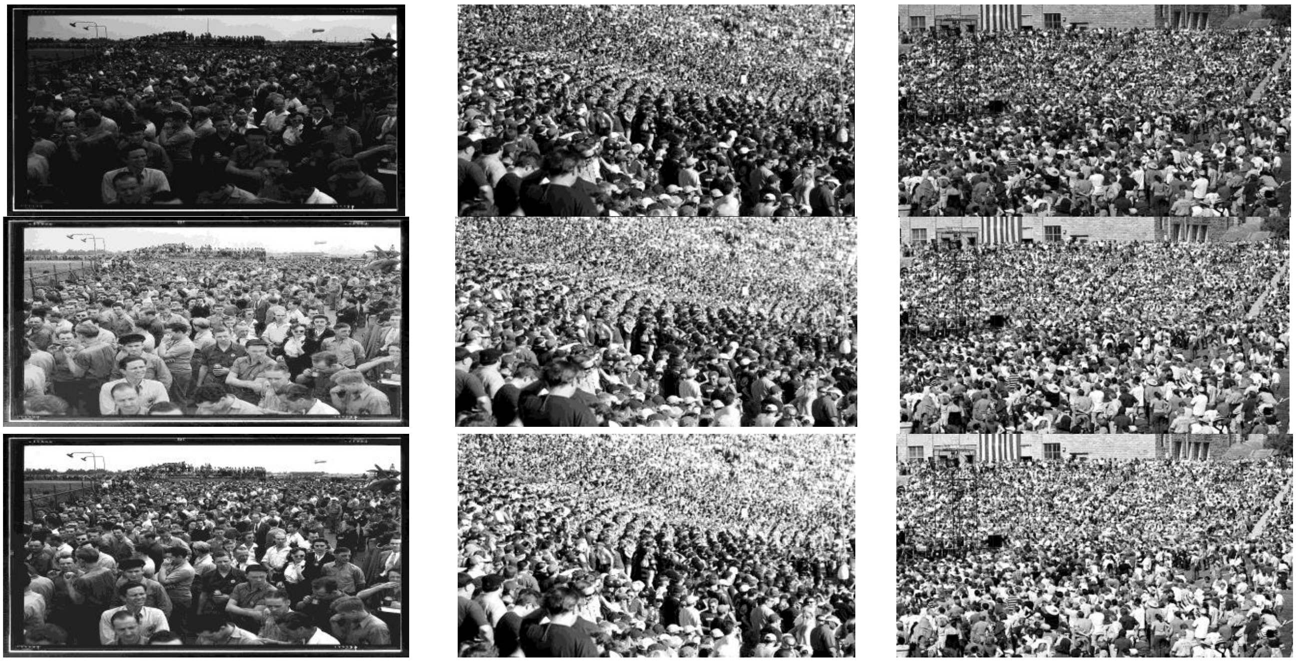
Fig 6: Comparison of 10 random images' average Contrast Improvement Index (CII) and Quality Index (QI) values based on proposed and Histogram Equalization method [48]

entropy to the original image, which shows the image information is preserved. A higher average gradient value reflects image quality improvement which is a measure of higher range an image has. Image entropy, on the other hand, represents the amount of information in an image [50]. For improvement in dense crowd images, both measures need to be high. That would represent higher image gray levels and information. In other cases, image quality is compromised. To analyse these results visually, Fig 7. shows some of the results.

Table 2 Comparison of average quantitative enhancement results of Images from UCF Dataset using different techniques

Method	Result Evaluation Measures					
	LD	*PSNR*	*Entropy*	*AMBE*	*QI*	*CII*
Original Image	-	-	7.57	-	-	-
Histogram Equalization	0.06	13.28	5.97	3.23	0.82	0.86
FGMT [46]	0.92	0.00	7.60	4.06	0.96	0.99
LLF [11]	0.97	0.45	7.46	12.80	0.87	0.89
Edge-aware Filter [12]	0.98	-0.12	7.5	12.3	0.93	1.06
Proposed Method	0.97	0. 5	7.63	4.34	0.90	0.96

Table 2 shows the average result of the dataset and compares different methods. It indicates that the proposed method has a good performance in terms of small AMBE, and a high QI, CII, PSNR and LD. Our method has a good performance in terms of securing image entropy; a measure of image information. Also, the gradients of the image are not compromised and they remain same or higher, in cases the boundaries of the crowd get enhanced. CII and QI indexes present a high value hence confirms an improved image contrast and quality. Table 1 illustrates that while our method successfully keeps image information, entropy, high, it does not always have a high average gradient as compared to Histogram Equalization. Albeit a higher average gradient, the HE method does not always result in a desired enhancement of the crowd image. The images are overexposed the detail of crowd heads or faces is lost. Therefore, the current methods are not suitable



(a) (b) (c)

Fig 7. Visual results of some of the test images from Table 1. The first row shows original images. Second row shows the result of HE. Result of the proposed method is shown in the third row. Fig 7(a) shows visual result when the proposed method achieves highest average gradient and entropy. 7(b)., row 2, illustrates the result where HE achieves better average gradient but lower entropy as compared to our method in row 3. In Fig 7(c) row 2 HE has lower average gradient but higher entropy as compared to the proposed method.

for image enhancement with the purpose of obtaining a good distinction among objects and humans in darker or over illuminated dense crowd scenarios. This is because perspective distortion and complex scenario details are generally not considered during image enhancement in these methods. In some images, such as those with outdoor scenario and dense crowd, where the people have a high global illumination, our results experiences noise. In such cases, the future work can integrate a more effective global measure to remove such problems and include diverse range of images, to increase the scope. Also, a more inclusive image quality measures can be explored which can better distinguish image enhancements.

V. Conclusion

In this paper, multi-scale-entropy information is used to enhance images using fuzzy logic. The images are mapped from spatial to fuzzy domain and enhanced with more adaptive and robust variables. This proposed algorithm can overcome the challenges of present image enhancement techniques against special case of dissimilar pattern across the image, such as dense crowd images where crowd is near or far from camera. Our approach used multi-scale local entropy information to enhance dense crowd images using fuzzy logic techniques. Consequently, the objective of enhancement is achieved regardless of the presence of several challenges such as varying illumination, perspective distortion and complex scenarios.

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