Performance Evaluation of Various Histogram Equalization Techniques on Thermal Images

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***Abstract*— This paper presents performance evaluation of various pre-processing techniques specifically on thermal images. Since thermal cameras often have lower resolution than RGB cameras, it might be difficult to successfully use their data for object recognition tasks. In the proposed work, the digital image processing-based techniques are applied on the thermal images to enhance the quality. The histogram equalization techniques along with their different variants, such as contrast limited adaptive histogram equalization, adaptive histogram equalization, plateau limit histogram equalization, brightness preserving bi-histogram equalization and minimum mean brightness error bi-histogram equalization (MMBEBHE) are utilized for the pre-processing. The performance is evaluated by computing the different parameters such as edge detection entropy score (EDES), peak signal to noise ratio (PSNR) & blind reference less image spatial quality evaluator (BRISQUE), along with the computation time on various sets of images. It is observed that the MMBEBHE gives us better result with the lowest BRISQUE score and highest EDES score.**

Keywords*— *Thermal image, Image enhancement, Histogram equalization

I. Introduction

Thermograms, also known as thermal images, are visual representations of an object's infrared radiation emission, transmission, and reflection [1, 2]. Due to their ability to offer temperature information, thermal cameras have shown to be a feasible option for object detection [3] and scene comprehension in challenging situations with a lot of background clutter or poor lighting. The resolution of current thermal cameras is often substantially lower than RGB cameras, making it challenging to properly utilize the data they provide for object recognition tasks. Researchers are working to improve the performance of thermal cameras by utilizing image-enhancement techniques and deep learning-based methods [3,4]. However, due to the decreased resolution of the thermal image, these methods may not always be successful. Deep learning-based methods have demonstrated notable performance gains ever since the the Super- Resolution Convolutional Neural Network (SRCNN) algorithm [4-8] was used to enhance images using deep learning. With the advent of widely used

autonomous mobile devices, it is becoming more difficult to be able to discriminate in poor lightning conditions. A thermal camera provides a wealth of temperature information that is less influenced by changing lighting or background noise. Applications that need precise object detection and high-quality images, such as autonomous cars and drones may find this challenging. Various image enhancement techniques [9-11], such as contrast adjustment and image brightening, have been created to improvise the quality of low-resolution images. However, it is preferable to use equalization techniques to improve the contrast of images before processing them with deep learning to reduce the model training time, increase the accuracy and speed up model inference. Histograms, which represent the distribution of an image's pixel values on a graph, are used in the HE approaches for image enhancement to change image's contrast In the proposed work, the thermal image is enhanced by pre-processing using the HE technique. The variants of HE is applied on different images and their efficacy is analysed using different parameters such as brightness referenceless image spatial quality evaluator (BRISQUE), edge detection entropy score (EDES), peak signal-to-noise ratio (PSNR) and computation time.

G. Yue et al. [12] used histogram equalization (HE) to preprocess the face image and further a CNN model LeNet-5 was deployed and they concluded that the algorithm had high recognition rate. Automated detection of diabetic retinopathy using deep learning was done by Lam et al. [13] by using CNNs on color fundus images. Additionally, this proposed work discovered that preprocessing with Contrast limited adaptive histogram equalisation (CLAHE) ensured fidelity and improves recognition of subtle features. In [14], HE was applied on pomegranate images in combination with wavelet denoising for preprocessing. Tasci et al. [15] proposed voting and preprocessing variations-based ensemble CNN model for tuberculosis detection. CLAHE was used as a pre-processing algorithm. Kim et al. [16] discussed brightness preserving bi-histogram equalization (BBHE) as an approach for image enhancement. The BBHE technique segments the histogram based on mean intensity value. The aforementioned survey discusses the various preprocessing technique applied before any machine or deep learning algorithms. The most prominent used technique is HE, therefore an urgent need arises to study the variants of HE and their efficiency needs to be analysed by using different comparative metrics. In the proposed work, the thermal image is enhanced by pre-processing using the HE technique. The variants of HE are applied on different images and their efficacy is analysed using different parameters such as BRISQUE, EDES, PSNR and computation time. The pre-processing of the thermal image is done in order to supress the undesired distortions in images and enhance the features of input images.

The paper is organised out as following- Section II provides the comparative analysis of different HE variants. Section III describes the parameters on which images are analysed. Section IV presents the experimental results of the variants of HE and its analysis by computing the BRISQUE, EDES, PSNR and computation time and subsequently the paper is concluded along with future scope of work in section V.

II. HISTOGRAM EQUALISATION TECHNIQUES

First, HE is a contrast-enhancing technique in the spatial domain. It is often used in medical imaging and photography. This technique is employed to modify the image's pixel values to better redistribute the intensity levels across the full range, producing a picture with greater contrast and more aesthetically pleasing colors. A grayscale input image $Y = y(i, j)$ with the L discrete levels where, the intensity levels of the image represented by $y(i, j)$ in the spatial domain (i, j) and the histogram of image Y is $H(X)$. Now, the probability distribution function (PDF) of Y in is defined in Eq.1

$$p(Y_k) = \frac{n_k}{N} \quad (1)$$

$$where, 0 \leq k \leq (L-1),$$

L is the total number of gray levels in an image. From the PDF (Y_i), the cumulative distribution function (CDF) of (Yi) is defined in Eq. 2 as:

$$C(Y_i) = \sum_{i=0}^{k} P(Y_i) \quad (2)$$

Note that $C(Y_{L-1}) = 1$

Moreover, the different HE variants are summarized as shown below.

A. Global Histogram Equalization

Global histogram equalization (GHE) increases the global contrast of the image to be processed. This method is suitable for images that are bright or dark. The sole disadvantage is that it is indiscriminate and boosts background noise contrast without taking into account usable signals which results in loss of information in input signals. To counter this disadvantage, adaptive histogram equalization (AHE) is used in which the image is broken up into little non-overlapping units called tiles. The histograms of each of these blocks are then equalized as usual. A histogram would therefore be limited to a restricted area in a short space.

B. Adaptive Histogram Equalization

AHE is especially helpful for images with uneven lighting or for images with low contrast that are challenging to view [17]. It uses local transformation, which enables the transformation function to be adjusted to the unique characteristics of each region, producing an image with increased contrast and more aesthetically pleasing hues. The transformation function is defined in Eq. (3) as:

$$f(Y) = Y_0 + (Y_{L-1} - Y_0)\, C(Y) \quad (3)$$

and the output image of the HE is listed in Eq. (4) as:

$$O = f(Y = \{f(Y(i,j)| \forall\, Y(i,j) \in Y\} \quad (4)$$

C. Contrast Limited Adaptive Histogram Equalization

The goal of CLAHE is to boost contrast while lowering the likelihood of over-enhancing the image and creating undesirable artifacts [18]. Similar to adaptive histogram equalization, CLAHE equalizes each block of the image individually by breaking it into smaller blocks or tiles. However, it also has a contrast-limiting step that stops further image improvement after a specific point. Overall, CLAHE is a helpful tool for improvising visual contrast while reducing the likelihood of overamplifying the noise in the image.

D. Brightness Preserving Bi-Histogram Equalization Technique

BBHE is a technique of image enhancement that divides the histogram of the input image in half by its mean. This yields two histogram ranges that do not overlap, which are then equalized independently. This allows the contrast of the image to be enhanced without changing its overall brightness. In this method, the histogram of the image is first segmented, then it chooses the plateau limits for both halves of the histogram, and then it just clips and equalizes each histogram separately. Let's now use the input meanY_m to divide the input image into the two sub-images $Y_l$and Y_u using the mathematically Eq. (5) (6) (7) and Eq. (8).

$$Y = Y_l \cup Y_u \quad (5)$$

where,

$$Y_l = \{Y(i,j)|\, y(i,j) \leq Y_m \forall\, y(i,j) \in Y\} \quad (6)$$

$$Y_u = \{\, y(i,j)|\, y(i,j) > Y_m \,\forall\, y(i,j) \in Y\} \quad (7)$$

and mean of the input image is calculated as:

$$Y_m = \frac{\sum_{i=0}^{l-1} i.p(Y_i)}{\sum_{i=0}^{l-1} p(Y_i)} \quad (8)$$

BBHE is effective if the input histogram has a quasi-symmetrical distribution around its mean. In these circumstances, the technique can preserve a portion of the image's natural brightness while still enhancing its contrast and enhancing its aesthetic appeal. In these cases, the technique can preserve a portion of the image natural brightness while still enhancing its contrast and making it more visually appealing.

E. Plateau Limit Histogram Equalization Technique

The Power-log Based PLHE algorithm is an innovative method specifically to overcome the shortcomings of conventional HE methods for enhancing infrared images. The concept of plateau limit and power log transformation is used for the enhancement. When pixel intensity values reach saturation in an infrared image, it creates plateau regions that lose important information and have low contrast. Traditional HE algorithms often fail to handle these plateau regions adequately, leading to suboptimal image enhancement. To overcome this limitation, the PLHE algorithm leverages a power-log transformation technique, which adjusts the dynamic range of pixel intensities based on the plateau limit. By applying a power function to the pixel intensities, the algorithm compresses the plateau regions while preserving the details in the non-saturated areas. This approach allows for more balanced enhancement, preventing over-amplification of noise and avoiding the loss of local information.

F. *Minimum Mean Brightness Error Bi Histogram Equalization (MMBEBHE)*

It is an effective, recursive, and integer-based solution to approximating the output mean as a function of threshold level. This makes it possible to implement the MMBEBHE method more effectively, which makes it appropriate for real-time applications. The MMBEBHE approach suggests dividing histogram by a threshold level which provide the least amount of absolute mean brightness error (AMBE). This can be computationally intensive, especially if there are several different gray levels. This may increase the computational cost of the MMBEBHE approach and limits its applicability for real-time application. MMBEBHE works as defined by the following steps:

1. The absolute mean brightness error for each of the threshold level is calculated.
2. The minimum threshold limit Y_T is evaluated, that gives minimum mean brightness error.
3. Finally, it separates the input histogram based on the Y_T evaluated in step 2 and histogram equalization is applied on each of the separated histograms as in BBHE. The performance of the equalization techniques is assessed on the basis of three parameters namely

III. PERFORMANCE PARAMETERS

The performance of the equalization techniques is assessed on the basis of three parameters namely:

A. *BRISQUE*- Blind/referenceless image spatial quality evaluator is highly suited for real-time applications because of its extremely low computational complexity. It's value usually lies in the range of [0,150] where, lower value of the score reflects better perceptual quality and higher value indicates bad quality of the image. Further, this parameter does not require reference image; this attribute is much suited in real time quality assessment of image.

B. *EDES*- Edge Detection Entropy Score is computed by using Canny edge detection method for edge detection followed by Shannon Entropy [19] based on strength of edges. A higher value of entropy means better information in an edge detected super resolution thermal image.

C. *PSNR*- Peak Signal to Noise Ratio is the ratio between the maximum potential power of an image and the maximum possible corrupting noise power that degrades the representational quality of the picture. The value of PSNR is directly proportional to quality of output image.

D. *Computation Time*- Computation time (also called execution time or running time) is the duration of time required to perform a computational process. It is a critical factor of consideration in the area of real time image processing applications. The computation time of any algorithm solely depends upon the complexity of the algorithm.

These four parameters are computed over the variants of HE and their efficacy is analysed in the next section.

PLHE uses the concept of power log transformation and concept of plateau limit for HE. On the basis of BRISQUE score, the image obtained by processing it with

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The proposed work presents the pre-processing of low-resolution thermal images obtained from a publicly available FLIR dataset [20]. The pre-processing technique such as histogram equalization using different variant is applied to enhance the thermal images. The histogram equalization technique, enhances the thermal image by dividing the image into smaller partitions or blocks. This allows for greater computational efficiency while increasing the accuracy and effectiveness of the image enhancement process. A criticism of these pre-processing techniques is that they continue to use histogram equalization to determine the contrast of each sub-partition. They consequently inherit all the negative effects of histogram equalization, including the possibility for excessive brightness and the loss of crucial image data. This may reduce these techniques' efficacy and render them less applicable to particular kinds of images. Table I represents parameters noted for two images after applying histogram equalization variants and further, these values are calculated for 30 images and average value is presented. Table II shows the input image and their equalized images processed by various algorithms. The BRISQUE score makes it clear that both the image's quality and its visual contrast has increased. A lower BRISQUE score reflects the better perceptual quality of an image. Additionally, by adjusting the histogram, EDES is improved, the higher the entropy score the more detailed image is obtained.

Further, the global contrast of the processed image is typically increased by GHE. For bright or dark images, this technique works well. To the contrary, an image with enhanced local contrast and more discernible fine details is the consequence of utilizing AHE. It is especially helpful for images with uneven lighting or for images with low contrast that are challenging to view. On the contrary, the

MMBEBHE, have better perceptual quality than others all having average BRISQUE score as 42.250736. The decreasing order of perceptual quality of images obtained after histogram equalization is listed as-

MMBEBHE > BBHE > PLHE > CLAHE > AHE

For some image types, particularly those with significant regions of uniform brightness or low contrast, AHE is frequently seen as being superior to conventional histogram equalization. For images with uneven lighting or images that are challenging to view because of low contrast, CLAHE is very helpful. Similar to AHE, CLAHE equalizes the histograms separately on each of the image's tiny blocks or tiles. The only difference is, it also has a contrast limiting step that stops further image improvement after a specific point. The foreground and background are enhanced separately in each frame and then fused into a new frame. This aids in avoiding the development of halos or other artifacts around the edges of visual objects. The PSNR ratio is used to evaluate the quality of the original and compressed pictures. Higher PSNR indicates the better quality of compressed or reconstructed image. MMBEBHE has average PSNR value of 30.13173 which has best quality of reproduced image as compared to other variants of HE. The only problem that lies with the MMBEBHE is the computation time. Since, MMBEBHE involves a recursive integer-based computation of AMBE. Calculating computation time is a crucially important statistic that may show us whether an algorithm is appropriate for the task at hand and completes in an acceptable amount of time, serving as a helpful guide for where additional optimization may be required. The MMBEBHE method's efficacy has been proved by simulation results utilizing test images with varying mean brightness levels, demonstrating that, it can handle situations where BBHE or standard histogram equalization are not the best solutions. Different images require different elements to be enhanced and thus, these methods are designed to cater the needs.

TABLE I. COMPARISON OF DIFFERENT VARIANTS OF HE ON THE BASIS OF DIFFERENT PARAMETERS ON VARIED SET OF IMAGES

S.No	HE Techniques	Performance Parameters			
		BRISQUE	**PSNR**	**EDES**	**COMPUTATION TIME (In Seconds)**
Image 1	Original image	152.46499	-	0.27815	Nil.
	GHE	26.94714	29.14048	0.30946	0.72536706
	AHE	146.84499	28.00715	0.32096	0.74839702
	CLAHE	143.98876	28.25652	0.28183	0.76096916
	BBHE	26.11534	27.91650	0.32862	0.76792621
	PLHE	48.123	27.8982	0.292	0.75945371
	MMBEBHE	26.09476	29.50443	0.33196	0.81707477
Image 2	Original image	139.03774	-	0.06362	Nil.
	GHE	41.21364	28.38096	0.06985	0.33510017
	AHE	170.58901	28.84657	0.06974	0.36934588
	CLAHE	142.23714	28.05992	0.33397	0.40403461
	BBHE	40.20175	35.93235	0.06578	0.39654588
	PLHE	40.19803	35.67389	0.070167	0.38399783
	MMBEBHE	40.08188	35.51526	0.070544	0.43184471
Average values of 30 images [20]	GHE	42.758882	28.497512	0.178936	0.41784472
	AHE	145.058086	28.152812	0.181442	0.45280625
	CLAHE	135.529286	28.383782	0.311736	0.47292733
	PLHE	46.871476	29.462774	0.1810054	0.44909576
	BBHE	42.56074	29.679212	0.181856	0.45917740
	MMBEBHE	42.250736	30.13173	0.1894144	0.48619065

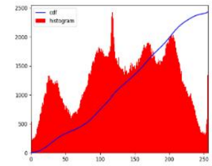
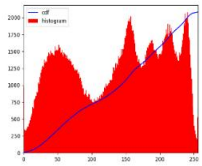
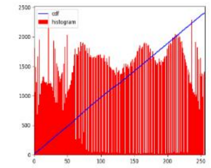
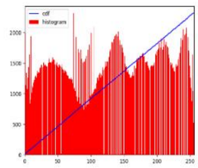
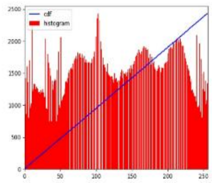
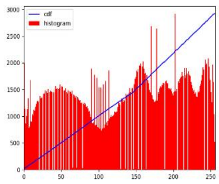
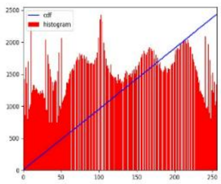
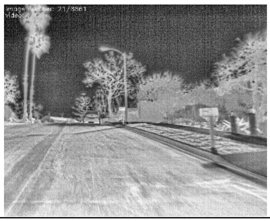
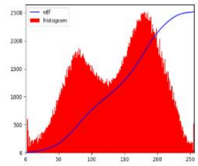
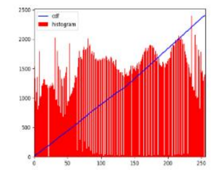
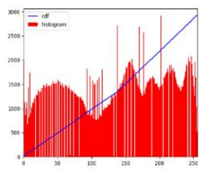
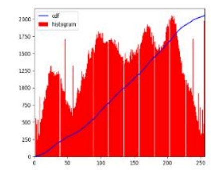
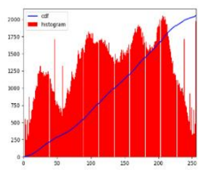
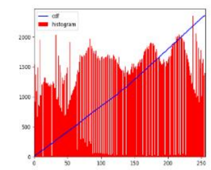
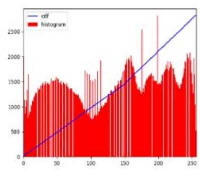
	Image-1	Histogram	Image-2	Histogram
Original Image				
GHE				
AHE				
CLAHE				
BBHE				
PLHE				
MMBEBHE				

TABLE II. REPRESENTATION OF VARIOUS HISTOGRAM EQUALIZATION VARIANTS AND THEIR RESPECTIVE HISTOGRAMS

V. CONCLUSION

This paper implemented different variants of HE techniques on thermal images and compared their performance by using parameters such as PSNR, BRISQUE, EDES and computation time. The analysis evidently shows that MMBEBHE gives finest result with the lowest BRISQUE score of 42.25 and also the highest EDES value of 0.89414. An effective, recursive and an integer-based solution to approximate the output mean as a function of threshold level has also been developed in this study which makes it possible to implement the MMBEBHE method more effectively, which makes it appropriate for real- time applications. However, there are certain limitation with the MMBEBHE technique, its average computation time is more than other methods due to its iterative nature. In future, for some enhancement and resolution improvement of thermal images, will be explored and attempt will be made for hardware realization of computationally efficient algorithms.

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