APPLICATIONS OF
MODELLING AND SIMULATION
http://arqiipubl.com/ams eISSN 2600-8084 VOL 4, 2020, 202-209

An Infrared Image Enhancement Technique Based on Neighborhood Wavelet Thresholding Coefficient for Multi-level Discrete Wavelet Transform

I. J. Umoh, G. Onuh*, T. H. Sikiru and D. Siman

Department of Computer Engineering, Faculty of Engineering, Ahmado Bello University, Zaria, Nigeria

*Corresponding author: onuhgabrielu@gmail.com

Submitted 03 April 2020, Revised 07 May 2020, Accepted 10 May 2020.

Abstract: The quality of infrared images is critical to a wide range of emerging applications and research. These images however suffer from low contrast and poor image quality. This research proposes an infrared image enhancement technique based on neighborhood wavelet thresholding coefficients for multi-level discrete wavelet transform (DWT). This technique will be implemented by first performing image pre-processing using Dabeuchies D4 filter. Following image preprocessing is multi-level wavelet decomposition based on the proposed neighborhood thresholding technique. Based on this thresholding technique, noise is eliminated and the sub-images undergo multi-level wavelet reconstruction to give an enhanced image as the final output. The results obtained were subjected to quantitative assessment by computing the peak signal-to-noise-ratio (PSNR) and discrete entropy (DE) values. From the assessment, the developed technique significantly eliminates noise with a better dynamic range.

Keywords: Image enhancement; Infrared image; Wavelet thresholding; Wavelet transform.

1. INTRODUCTION

Infrared images are applied in various fields and new applications are constantly being developed. Some of the areas of application are; military, medicine, industries and manufacturing, security and defense as well as space applications [1]. The relevance of infrared images in various applications makes the visual quality of these infrared images critical. The primary factor that affects the quality of infrared images is the presence of noise [2]. It is well known that the signal-to-noise ratio as well as the contrast of infrared images is low[2, 3]. These two inherent factors make the processing of infrared images challenging. The principal sources of noise in infrared images are; atmospheric conditions, the infrared sensors and interference of the signal processing circuit. Based on the infrared sensor technology, the problem may be related to photoelectric conversion (in photo-detectors) or temperature fluctuation noise (in thermal-detectors) and also the influence of the manufacturing process [5]. This causes non-uniformity in the infrared detector, which is revealed by the varied response of the image pixels. This non-uniformity if not properly corrected, maybe the major source of noise in infrared images. Also environmental and atmospheric conditions during capturing also constitute noise [4, 5].

Conventional infrared image enhancement techniques can be grouped into two main classes based on the method of intensity mapping. They are; global intensity mapping and local intensity mapping. In the global intensity mapping technique, histogram equalization is the commonly used enhancement technique, which manipulates the occurrence probability histogram to differentiate the intensity levels with high probability from the neighbouring intensity levels[8]. However over-enhancement of the background image has being reported with histogram equalization [9]. This is because the intensity levels with high probability usually are the background pixels that occupy most of the dynamic range and they are dramatically enhanced, while the intensity levels with low probability are related to small objects and are most times suppressed or even lost[10]. Several improvements have been made to resolve the issue of over-enhancement in histogram equalization. The plateau based techniques, such as plateau histogram equalization [11], double plateaus histogram equalization and adaptive double plateau histogram equalization [12] techniques based on histogram segmentation, introduced to limit the probability of intensity levels of background and increase the low probability to preserve image details . Also, other techniques were developed as alternative solutions to deal with the over enhancement of histogram equalization, such as Brightness-preserving Bi-histogram equalization [13], Range Limited Bi-Histogram Equalization [14], Adaptive Histogram Partitioning [15]. Still, the modified histogram-based techniques do not adequately reduce the gap of probabilities between intensity levels, and the probabilities of objects-related intensity levels are still less or equal to the probabilities of background-related levels. As a result, the outputs of the probability histogram equalization based techniques, the contrast between the image objects and the image background is not sufficiently enhanced, which is unsatisfactory for infrared image applications.

To obtain better results during image interpretation and analysis, infrared images should be enhanced with effective techniques. This research proposes an infrared image enhancement technique based on neighborhood thresholding coefficients for multi-level discrete wavelet transform (DWT). This technique effectively eliminates noise and enhances image details with a better dynamic range.

2. METHODOLOGY

The proposed infrared image enhancement is based on enhancement in the frequency domain. A neighborhood wavelet thresholding coefficient was developed for multi-level wavelet transform which was used to enhance a dataset of infrared images. The flowchart for the proposed technique is shown in Figure 1 and the methodology is further explained in the rest of this section.

2.1 Multi-level Discrete Wavelet Transform

Wavelet transformation is in three stages: a linear forward wavelet transform, a thresholding step and a linear inverse wavelet transform in two levels. Based on the proposed wavelet thresholding technique, infrared image enhancement is carried out. The dataset used for this algorithm were acquired from Dynamic Graphics Project laboratory public database of infrared images [9]. After the dataset was acquired, the test images were pre-processed using Daubechies D4 filter before undergoing wavelet transformation. The dataset contains eight test images namely; leg, building, guardrail, computer, car, cabinet, residence and room. The images in the dataset are 8-bit gray scale infrared images as shown in Figure 2.

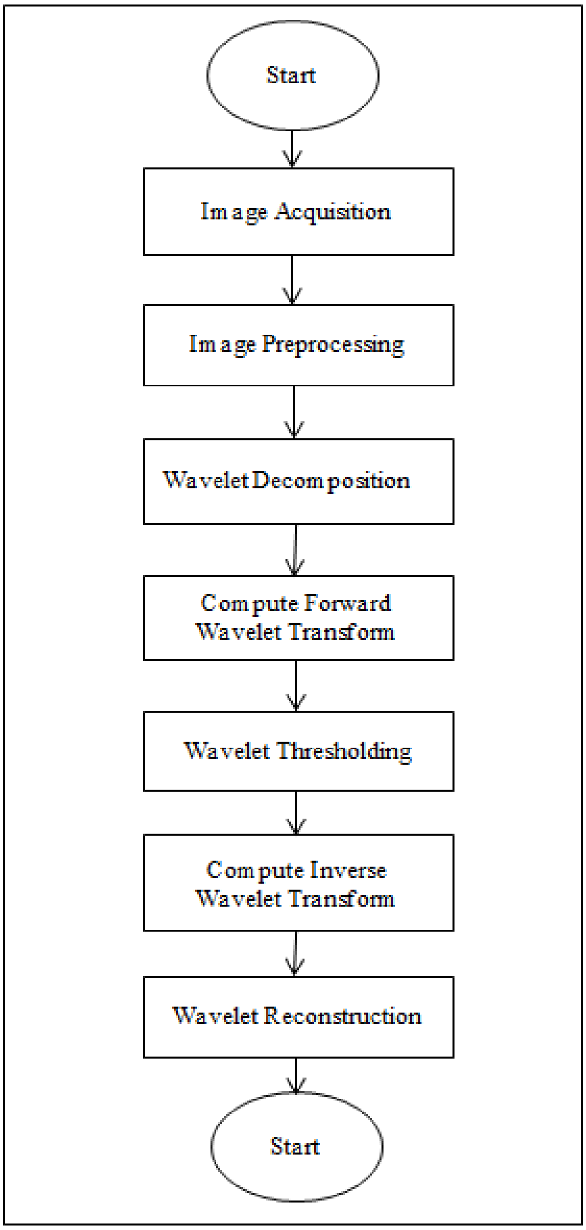

Figure 1. Flowchart for the proposed enhancement technique

(a) Leg

(b) Building

(c) Guardrail

(d) Computer

(e) Car

(f) Cabinet

(g) Residence

(h) Room

Figure 2. Dataset of original test images

2.2 Wavelet Thresholding Technique

Wavelet thresholding is a key determinant to obtaining a high quality output during wavelet decomposition. The wavelet thresholding technique proposed is based on the noise variance, universal wavelet threshold and neighboring coefficients for multilevel wavelet transformation. The equation for computing noise variance is given as

$$\sigma = \frac{mean\ (|x_i|)}{0.6745} \tag{1}$$

where σ is the noise variance, x_i is the detail coefficient and 0.6745 is the scaling factor for normally distributed data [16]. A universal threshold, function of noise level σ and length of data array *N*, is used to estimate the threshold level λ expressed as

$$\lambda = \sigma\sqrt{2\log(N)} \tag{2}$$

The proposed thresholding function T^{λ} is determined based on neighboring coefficients. The wavelet coefficient A_k is modified such that two neighboring coefficients are considered as

$$A_k^2 = a_{k-1}^2 + a_k^2 + a_{k+1}^2 \tag{3}$$

Based on the neighboring coefficients, the thresholding function T^{λ} is expressed as

$$T^{\lambda} = \begin{cases} a_k = 0, & a_k^2 \leq \lambda^2 \\ a_k = a_k(1 - \frac{\lambda^2}{a_k^2}), & a_k^2 > \lambda^2 \end{cases} \tag{4}$$

The proposed wavelet thresholding technique is implemented during the multi-level wavelet decomposition of the original images.

2.3 Wavelet Transformation

Discrete wavelet transform is used for decomposing the original test image. At every level of the multi-level wavelet decomposition, four sub-images are obtained namely; approximation, vertical details, horizontal details and diagonal details. For the next level of decomposition, the approximation sub-image is further decomposed into four sub-images of approximation, horizontal, vertical and diagonal details. Figure 3 shows the multi-level decomposition of original test image (leg). Multi-level inverse wavelet transform is used for reconstruction of the image. It is implemented by taking the wavelet coefficients from a previous decomposition matrix and performing the inverse wavelet transform.

2.4 Performance Evaluation

The performance of the proposed technique was evaluated using Peak-Signal-to-Noise Ratio (PSNR) and Discrete Entropy (DE) as performance metrics. PSNR and DE are discussed in this subsection.

2.4.1 Peak Signal-to-Noise Ratio

Peak signal-to-noise ratio is a metric for evaluating the quality of an enhanced image by computing the ratio of maximum signal power to maximum noise power. It is measured on a logarithmic scale in decibels (dB). Mean Square Error (MSE) which is the average of the squared difference of the intensities of the original and enhanced image is used to compute PSNR. The larger the PSNR value of an image the higher the image quality [17]. The equations for PSNR and MSE are stated in Equations 5 and 6.

$$\mathrm{PSNR} = 10\log_{10}(\frac{Max^2}{MSE(O,I)}) \tag{5}$$

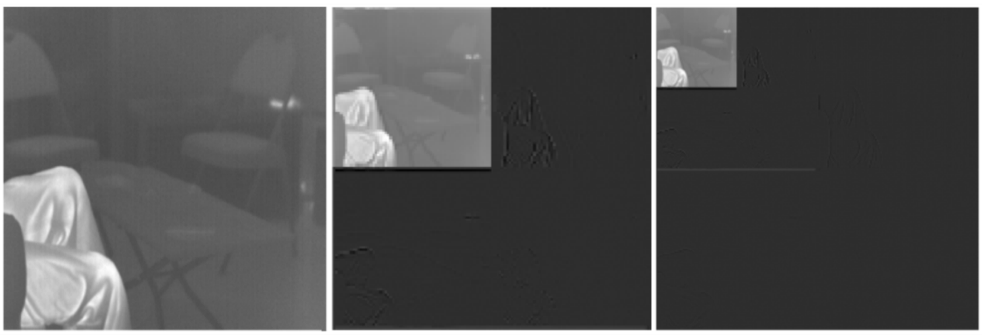

Figure 3. Multi-level wavelet decomposition of the original test image (leg)

where Max denotes the maximal gray level and $Max = 255$ for 8-bit digital images. $MSE(O, I)$ is the mean square error between the output O and input I, which is defined as

$$MSE = \frac{1}{MN} \sum_{x=0}^{M-1} . \sum_{y=0}^{N-1} (O_{(x,y)} - I_{(x,y)}) \tag{6}$$

where M and N are the total numbers of rows and columns respectively, and x and y are the pixel values across the rows and columns.

2.4.2 Discrete Entropy

Discrete Entropy (DE) is a statistical index that characterizes the information amount contained in an enhanced image. It was employed to measure the degree of over-enhancement in our experiment. The DE of an image is expressed in Equation (7) as

$$\mathrm{DE} = \sum_{s=0}^{L-1} -P_s \log_2 P_s \tag{7}$$

where s is image pixel, L is the total number of pixels and P_s is the probability of event s. A larger DE value means fewer gray levels are merged, leading to a clearer visual performance [18].

3. RESULTS AND DISCUSSION

The enhanced infrared images based on conventional techniques such as BBHE, DPHE, AHP and the proposed technique are presented in Figure 4 for qualitative assessment.

BBHE DPHE AHP Proposed

(a) Leg

(b) Building

(c) Guardrail

(d) Computer

Figure 4. Enhanced images using BBHE, DPHE, AHP and the proposed technique

Illustrated in Figure 4 are the enhanced output of leg, building, guardrail, car, computer, cabinet, residence and room. The approach of decomposing the original image into its frequency components based on the proposed thresholding technique outputs the horizontal, vertical, diagonal and approximation constituents of the image thereby making it possible to effectively remove the inherent noise present in the image and produce an enhanced output. The proposed technique improved the visual quality of the images as show in Figure 4a (iv). The same result was obtained for all eight test images present in the dataset. The image details and features of the dataset were adequately enhanced with a better dynamic range. The PSNR and DE values for all eight test images using BBHE, DPHE, AHP and proposed technique are presented in Tables 1 and 2.

Based on the results presented in Table 1, infrared image enhancement based on the proposed technique has high PSNR values. The range of PSNR values obtained from the eight enhanced images is from a minimum value of 18.2091 for guardrail to a maximum value of 27.5500 for leg, also the dataset has an average PSNR value of 20.96. Given that the larger the PSNR value the higher the quality of the enhanced image leading to a clearer visual performance in the final output, the proposed technique outperforms conventional techniques such as BBHE, DPHE and AHP in terms of PSNR.

From the results presented in Table 2, infrared image enhancement based on the proposed technique has high DE values. The range of DE values obtained from the eight enhanced images is from a minimum value of 5.5042 for residence to a maximum value of 7.2166 for guardrail, also the dataset has an average DE value of 6.49. A large DE value means fewer gray levels were merged leading to a better dynamic range; therefore the proposed technique outperforms conventional techniques such as BBHE, DPHE and AHP in terms of DE.

Table 1. Comparison of PSNR values of test images

No.	Test Images	BBHE	DPHE	AHP	PROPOSED TECHNIQUE
1	Leg	14.2202	25.2335	24.6008	27.5500
2	Building	12.6611	16.8048	16.8685	18.5102
3	Guardrail	13.2453	13.1659	16.7550	18.2091
4	Car	13.4511	15.3592	16.9767	18.6048
5	Computer	11.4154	27.6319	21.4629	23.4305
6	Cabinet	12.5129	12.0847	16.5403	18.4239
7	Residence	12.0603	18.8433	18.5197	20.1963
8	Room	13.2009	12.5104	20.5891	22.7962

Table 2. Comparison of DE values of test images

No.	Test Images	BBHE	DPHE	AHP	PROPOSED TECHNIQUE
1	Leg	5.4267	5.3053	5.4650	6.8558
2	Building	5.2030	5.1544	5.5059	6.5238
3	Guardrail	5.5252	5.3767	6.0788	7.2166
4	Car	5.6892	5.3767	5.7270	6.9979
5	Computer	4.1793	4.1892	4.4657	5.5885
6	Cabinet	5.3335	5.6247	5.6769	6.7230
7	Residence	4.6137	4.7578	4.7814	5.5042
8	Room	5.6513	5.4883	5.6247	6.5380

4. CONCLUSIONS

To address the challenge of poor image quality in infrared images, an infrared image enhancement technique based on neighborhood wavelet thresholding coefficient for multi-level wavelet transform is presented. The proposed algorithm was tested on a dataset obtained from Dynamic Graphics Project Laboratory database of infrared images and compared with conventional approaches. Based on the results obtained, image details were effectively enhanced with a better dynamic range; also the proposed technique shows significant improvement when compared with conventional techniques.

REFERENCES

[1] M. Jiang, Edge enhancement and noise suppression for infrared image based on feature analysis, *Infrared Physic & Technology*, 91, 2018, 142–152.

[2] L. Liu, L. Xu and H. Fang, Infrared and visible image fusion and denoising via l_2 - l_p norm minimization, *Signal Processing*, 172, 2020, 107546.

[3] N. Bhatia and T. Kumar Rawat, An improved technique for image contrast enhancement using wavelet transforms, *Proceedings of International Conference on Smart Technologies for Smart Nation (SmartTechCon 2017)*, Bengaluru, India, 2017, 815–819.

[4] L. Zhao, H. Bai, J. Liang, A. Wang, B. Zeng and Y. Zhao, Local activity-driven structural-preserving filtering for noise removal and image smoothing, *Signal Processing*, 157, 2019, 62–72.

[5] J. Chen, X. Li, L. Luo, X. Mei and J. Ma, Infrared and visible image fusion based on target-enhanced multiscale transform decomposition, *Information Sciences,* 508, 2020, 64–78.

[6] J. Ma *et al.*, Infrared and visible image fusion via detail preserving adversarial learning, *Information Fusion*, 54, 2020, 85–98.

[7] S. Budzan and R. Wyżgolik, Remarks on noise removal in infrared images, *Measurement Automation Monitoring*, 61(6), 2015, 187–190.

[8] V. Voronin, S. Tokareva, E. Semenishchev and S. Agaian, Thermal image enhancement algorithm using local and global logarithmic transform histogram matching with spatial equalization, *Proceedings of IEEE Southwest Symposium on Image Analysis and Interpretation*, Last Vegas, USA, 2018, 5–8.

[9] J. Huang, Y. Ma, Y. Zhang and F. Fan, Infrared image enhancement algorithm based on adaptive histogram segmentation, *Applied Optics*, 56(35), 2017, 9686.

[10] B. Wang, L. L. Chen and Y. Z. Liu, New results on contrast enhancement for infrared images, *Optik*, 178, 2019, 1264–1269.

[11] V. E. Vickers, Plateau equalization algorithm for real-time display of high-quality infrared imagery, *Optical Engineering*, 35(7), 1996, 1921.

[12] S. Li, W. Jin, L. Li and Y. Li, An improved contrast enhancement algorithm for infrared images based on adaptive double plateaus histogram equalization, *Infrared Physic & Technology*, 90, 2018, 164–174.

[13] S. Der Chen and A. R. Ramli, Minimum mean brightness error bi-histogram equalization in contrast enhancement, *IEEE Transactions on Consumer Electronics*, 49(4), 2003, 1310–1319.
[14] C. Zuo, Q. Chen and X. Sui, Range limited bi-histogram equalization for image contrast enhancement, *Optik*, 124(5), 2013, 425–431.
[15] M. Wan, G. Gu, W. Qian, K. Ren, Q. Chen and X. Maldague, Infrared image enhancement using adaptive histogram partition and brightness correction, *Remote Sensing*, 10(5), 2018, 682.
[16] Y. Binbin, An improved infrared image processing method based on adaptive threshold denoising, *EURASIP Journal on Image and Video Processing*, 2019, 5(2019).
[17] R. D. Pai, P. Srinivashalvi and P. Basavarajhiremath, Medical color image enhancement using wavelet transform and contrast stretching technique, *International Journal of Scientific and Research Publications*, 5(7), 2015, 1-7.
[18] M. Wan, G. Gu, W. Qian, K. Ren, Q. Chen and X. Maldague, Particle swarm optimization-based local entropy weighted histogram equalization for infrared image enhancement, *Infrared Physic & Technology*, 91, 2018, 164–181.