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An Enhanced Type II Fuzzy Set Algorithm for Satellite Images Contrast Improvement

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Abstract

Satellite images contain detailed information that is of great importance in the field of remote sensing. However, these images often suffer from low contrast due to numerous atmospheric obstructions. However, many methods have been developed to enhance these images but most of them have not achieved satisfactory results. Therefore, satellite imagery processing remains an active area of research. Hence, this research has proposed a modified type of II fuzzy set algorithm to improve the contrast of grayscale and color satellite images appropriately so as to maintain the overall brightness of the image and also give natural colors. The proposed algorithm employs a modified Hamacher t-conorm with a new lower and upper ranges. The resulting output is further processed based on sigmoid function and contrast stretching techniques to produce the final improved image. The proposed algorithm's performance was assessed with natural degraded satellite images and compared with six other methods as well as the evaluation of the comparison's outcomes was done using two metrics in addition to the processing time. It scored the optimum in both metrics, which obtain (20.907) in BRISQUE and (3.467) in NSS. The experimental results of the proposed algorithm demonstrated outstanding performance compared to the other methods as it produced images with clear details and natural colors without increasing image brightness.

Keywords: contrast enhancement, remote sensing, type-ii fuzzy, satellite images enhancement, sigmoid function.

1 Introduction

Image preprocessing is crucial in image processing because it facilitates subsequent processing. One of the most important preprocessing methods is image enhancement [1], a fundamental step in many applications such as medical imaging, meteorology, defense operations, and satellite imagery [2]. This enhancement clarifies image information and details, making them easier for viewers to understand. Image enhancement include smoothing, sharpening, contrast enhancement (CE), noise removal, etc.[1].

The tremendous advancement in sensor technology for astronomy, weather forecasting, and geographic information have made improving satellite imagery extremely important [3]. Satellite images contain detailed geographic information about the characteristics of the imaged area [4]. These images are affected by numerous atmospheric factors and obstacles, such as reduced resolution, lower contrast, distortion, and noise, due to being captured from great distances and high altitudes [5]. Satellite image's quality rely on many factors. The contrast is the most important factor, which is the difference in the reflected luminance component from two adjacent surfaces [6]. When the light intensity values (contrast) of an image become excessively concentrated within a limited dynamic range, the differences between pixels become very small, leading to loss of visual detail in those areas. This results in reduced contrast and difficulty distinguishing features in the image, necessitating the application of contrast enhancement techniques to redistribute intensity levels and restore lost visual information [7]. The primary goal of (CE) is to improve image information and highlight hidden details in order to accurately represent all the features present in the image, which is crucial in applications [7].

Numerous contrast enhancement methods have been proposed, but most produce common distortions such as increased image brightness, color shift, and loss of details. One of these methods that proposed in 2014 [15] to improve image contrast based on fuzzy concept. It is characterized by its

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simplicity, employing straightforward processing steps, making it suitable for many image processing applications. However, this algorithm suffers from several drawbacks: it improves contrast very slightly, increases the brightness of overexposed areas of the image, increases the overall image brightness, and produces images with lighter colors. These drawbacks result in losing of some image information. Therefore, it is crucial that satellite image contrast enhancement methods not only improve contrast but also minimize pixel distortion across the entire image and maintains its brightness [8]. To achieve this, an amended satellite image contrast enhancement algorithm based on Type-II Fuzzy concept has been developed. It enhances the contrast and at the same time preserve image brightness and restore its natural colors. In the first step of the proposed algorithm, the input image is fuzzified, then its local statistics is computed. After that, it uses a modified Hamacher t-conorm with new lower and upper ranges. Then the output from this step, in turn, undergoes further processing using sigmoid function method and contrast stretch method to produce the final improved image. The main contribution of this study involves developing a previous algorithm based on the Type-II Fuzzy concept for the purpose of improving the contrast of satellite images efficiently and quickly without causing any unwanted distortions in the resultant image, through the use of uncomplicated and non-repetitive techniques to avoid increasing the brightness of the image and also avoided noise amplification. Testing the proposed algorithm is done on a set of real degraded satellite image to prove its performance. The comparison with six methods is made. the evaluation process was based on two well-known metrics namely Blind Referenceless Image Spatial Quality Evaluator (BRISQUE), Natural Scene Statistics (NSS). The comparison results proved the superiority of the proposed algorithm over other methods, as it produced satellite image of satisfactory quality, appropriate brightness, and natural colors without any errors or unwanted distortions.

The rest of this research is as follow: section 2 illustrates many studies related to this research, section 3 provides a detailed explanation of the proposed algorithm, the results of tests and comparisons of the proposed algorithm are explained in section 4, while section 5 contains the conclusion and future work.

2 Related Works

Many researchers in recent years have presented methods to address the low contrast of satellite images. In 2018, spatially adaptive gamma correction method was proposed to enhance the satellite image. In this method, the input image is decomposed into base and details layers. As for the base layer, the uneven intensity of it was corrected using a proposed histogram-based gamma factor. While the details layer improved through an adaptive correction parameter, which is computed based on the standard deviations and bit depth between the origin and enhanced base layers. Combining the two enhanced layers result in the final improved image [9]. In 2019, simple, spatial based method for aerial and satellite image enhancement was developed. Firstly, luminance normalization process is done on input image's brightness scale using NL- fractional stretching functions. Also, the input image is processed using local contrast stretching to enhance the finely edges and details. The two results fused using a weighting fusion, enabling the adjusting of the best features in the same visualization. Finally, multiscale Retinex algorithm was applied to get the final image [10].

In 2020, an optimized contrast stretch method was presented. This method utilized the Bat optimization algorithm for automated control parameters selection in the transformation process. Its performance compared with other optimization algorithm, it surpassed them in the improvement process [11]. In 2023, a novel algorithm to enhance dark satellite image was proposed. The algorithm begins by read the input image, segment it to different clusters using fuzzy semi-supervised clustering. Next, each cluster's lower and upper bound are determined. These bounds then used to set the gray level transformation for every image pixel. After that, a sub-algorithm was implemented to do the grey level transformation for each (R,G,B) channel to a new gray level which its value aggregated with the weight related to the cluster membership value. This approach enhanced the image and preserve its features [12]. Also, in 2023, an adaptive contrast improving method was presented. The method relies on NL-transfer function with the histogram approaches. Its work by converting the RGB image to CIE LAB color model. Only the L-channel from it was processed using NL-transfer function and then CALAHE. After that, the enhanced L-channel combined with the

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remaining channels. The final image obtained by converting the resultant image to RGB color model [13].

In 2024, a new approach to enhance satellite image was introduced. The approach combines the NLM filter with CALAHE to get the strength of the two techniques. It begins with reading the input image, converting it to Lab color space to apply NLM filter. which preserve image structure, then turn it to RGB. After that, the CALAHE method was applied to improve the local contrast to enhance image features visibility. This combination produces images with good clarity and details [14]. The problems identified in related studies are as follows: some methods may lead to increased image brightness, resulting in washed-out colors. Others require adjusting a large number of parameters, while still others are computationally complex and costly. Therefore, the field remains open for research into better methods to improve the contrast of satellite images.

3 The Proposed Algorithm

In 2014, type-II fuzzy set algorithm (Fuzzy-II) was proposed to improve the image contrast. The algorithm works through several uncomplicated steps, where the image is initially fuzzified using the following equation (1) [15]:

$$f_{(x,y)} = \frac{p_{(x,y)} - \min(p_{(x,y)})}{\max(p_{(x,y)}) - \min(p_{(x,y)})} \tag{1}$$

Where $p_{(x,y)}$ is the input image, x and y are the coordination of image, min and max are the minimum and maximum values in input image, $f_{(x,y)}$ is the fuzzified image. Then the two Hamacher t-conorm ranges, which are the upper $u_{(x,y)}$ and lower $w_{(x,y)}$ ranges are determined based on the following equations (2) and (3):

$$w_{(x,y)} = \left(f_{(x,y)}\right)^{1/\alpha} \tag{2}$$

$$u_{(x,y)} = \left(f_{(x,y)}\right)^{\alpha} \tag{3}$$

where (α) is a factor that adjusts the amount of enhancement, it should be $0<\alpha\leq 1$. Then, based on the upper and lower ranges, the Hamacher t-conorm was calculated to get the enhanced image using the following equation (4):

$$h_{(x,y)} = \frac{u_{(x,y)} + w_{(x,y)} + (\lambda - 2) \cdot u_{(x,y)} \cdot w_{(x,y)}}{1 - (1 - \lambda) \cdot u_{(x,y)} \cdot w_{(x,y)}} \tag{4}$$

where (λ) is the mean image pixel values of the fuzzified image, $h_{(x,y)}$ is the final-enhanced image, (.) is the multiplication process. This algorithm characterized by its computational simplicity, making it suitable for various image processing applications. However, despite its simplicity, it has several drawbacks. For example, it only slightly improves contrast, over-brightens the image, especially in highly illuminated areas, leading to a loss of image's details and information. Furthermore, images processed with this algorithm tend to have very pale and lifeless colors. This presents a significant opportunity for further development and improvement of the algorithm's performance, aiming to achieve better contrast and more natural colors while maintaining the overall brightness of the image.

In this research, an amended algorithm based on type-II fuzzy set concept is developed to enhance the contrast of satellite images. The input image $p_{(x,y)}$ is fuzzified using (Eq.1) to get $f_{(x,y)}$, then, the standard deviation σ for $f_{(x,y)}$ is computed using the following equation (5) [16]:

$$\sigma = \sqrt{\frac{1}{n-1} \cdot \sum_{i=1}^{n} (f_i - \mu)^2} \tag{5}$$

where μ is the mean of $f_{(x,y)}$, f_i is the vector corresponding to $f_{(x,y)}$, n is the total element in f_i. After that, new upper $\hat{u}_{(x,y)}$ and lower $\hat{w}_{(x,y)}$ ranges of the Hamacher t-conorm are computed, the

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new upper here represents a modified Gompertz distribution function which is used for enhance the brightness. The origin equation (6) of it is as follow [17]:

$$GD = 1 - exp\left(-\frac{\eta}{\gamma}(exp(\gamma.p) - 1)\right) \tag{6}$$

where η is the brightness enhancement parameter, $\eta > 0$, $\gamma=1$. In this research, a modified Gompertz distribution function is used to adjust image brightness using the following equation (7):

$$\hat{u}_{(x,y)} = 1 - exp\big(-(\delta \cdot 0.1) \cdot exp\big(f_{(x,y)}\big) - 1\big) \tag{7}$$

Where δ is the brightness parameter, $\delta > 0$. Applying Eq.7 altered the brightness and the contrast of the $f_{(x,y)}$. While the new lower represents a modified sigmoid function, the origin equation (8) of sigmoid function is as follow:

$$SF = \frac{1}{1+e^{-p}} \tag{8}$$

The modified sigmoid function used here to provide non-linear contrast enhancement computed using the following equation (9):

$$\hat{w}_{(x,y)} = \left(\frac{1}{1+e^{-f_{(x,y)}}}\right)^{5.9} \tag{9}$$

The new Hamacher t-conorm is computed using the following equation (10):

$$\hat{h}_{(x,y)} = \frac{\hat{u}_{(x,y)} + \hat{w}_{(x,y)} + (\sigma-2)\cdot\hat{u}_{(x,y)}\cdot\hat{w}_{(x,y)}}{1+(\sigma-1)\cdot\hat{u}_{(x,y)}\cdot\hat{w}_{(x,y)}} \tag{10}$$

The resultant image is further enhanced using Eq. (11) but as following:

$$T_{(x,y)} = \frac{1}{1+e^{-\hat{h}_{(x,y)}}} \tag{11}$$

Finally, a normalized min-max function is applied for stretch image contrast to full dynamic range using the following equation (12) [18]:

$$N = \frac{T - min(T)}{max(T) - min(T)} \tag{12}$$

where min and max are the least and greatest amounts, N is the final enhanced image of the proposed method. The flowchart diagram of the proposed algorithm steps illustrated in Figure 1. The proposed algorithm was tested by conducting an ablation study, which involved varying the value of the parameter responsible for adjusting image brightness and observing its effect on the algorithm's performance. This parameter is δ. Figure 2 shows that the image brightness changes with the value of δ, reducing the brightness as the δ value decrease. In Figure 2(b), when δ=5, the resulting image is nearly bright, while the image bright reduced as the δ value become near the 0. Suitable brightness in this image is achieved when (3<δ<0.5) as shown in Figure 2 from (f) to (k), depending on the processed image and its lighting conditions. Therefore, the only drawback of the proposed algorithm is that the value of δ must be chosen manually to obtain the desired result for each image.

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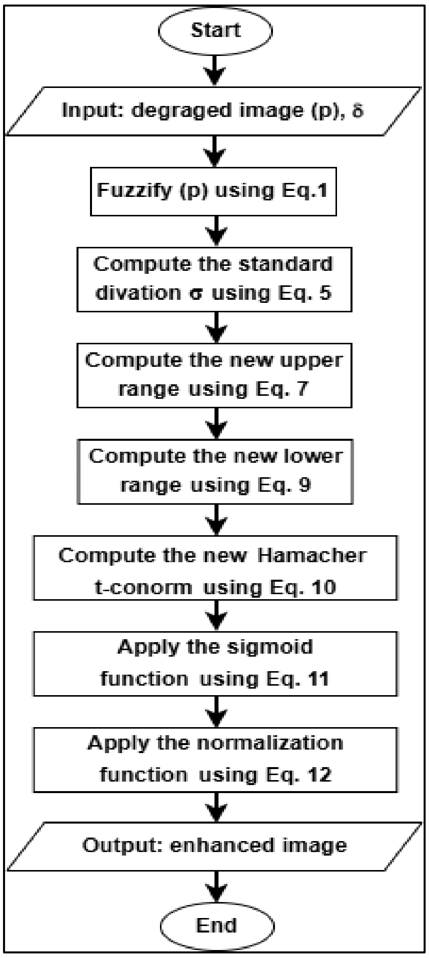

Figure 1 The flowchart diagram of the proposed algorithm

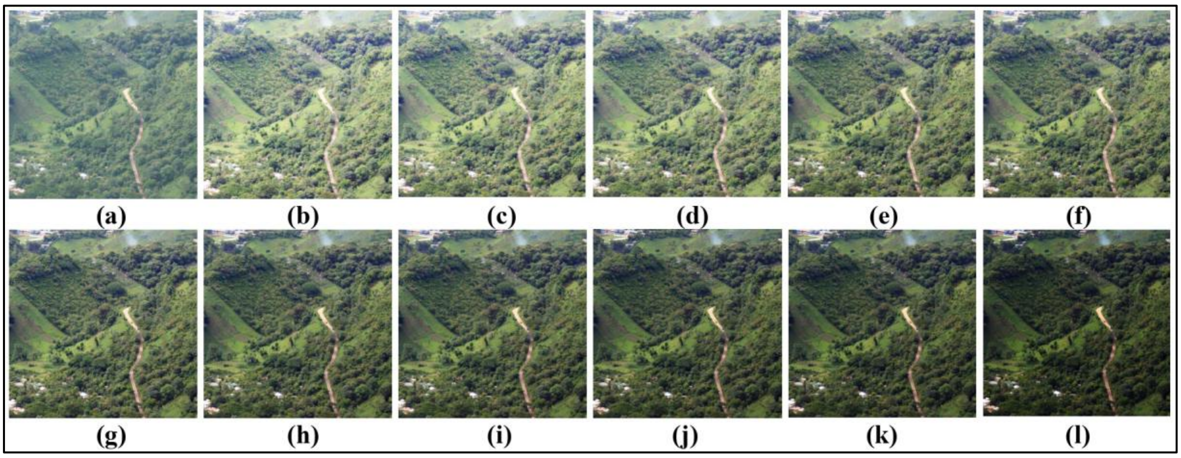

Figure 2 Applying the proposed algorithm with different δ values. (a) natural degraded image; (b-l) the enhanced images using: (b) δ=5; (c) δ=4.5; (d) δ=4; (e) δ=3.5; (f) δ=3; (g) δ=2.5; (h) δ=2; (i) δ=1.5; (j) δ=1; (k) δ=0.5; (l) δ=0.1;

4 Results and Discussion

This section includes detailed information about the dataset, tests, comparison with other methods and metrics used, as well as computer specifications. The dataset used in this research was obtained from Remote Sensing Satellite Images dataset, available at https://www.kaggle.com/datasets/umeradnaan/remote-sensing-satellite-images?resource=download. A collection of satellite images captured by remote sensing satellites, totaling approximately (1000) jpg

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images of size (640×640), including forest areas, bodies of water, urban areas, agricultural fields, and more. As for the tests, the proposed algorithm was tested on a set of low-contrast satellite images, and Figure 3 shows some of the results of applying the proposed algorithm as well as the origin Fuzzy-II algorithm on low-contrast images. The comparison process involves six methods that uses different concepts to enhance the contrast namely: origin Fuzzy-II [15], ACO-SA-GA [19], AGCWD [20], FCCE [21], SSR [22], SMIPC [23]. The comparison results were evaluated using two metrics, BRISQUE [24] and NSS [25]. The BRISQUE (Blind Referenceless Image Spatial Quality Evaluator) evaluates the overall quality of the resultant image through some statistical measurements of its brightness. The NSS (Natural Scene Statistics) evaluate contrast naturalness using some characteristics like moment and entropy. Lowest score in BRISQUE with highest score in NSS indicates high quality image with more natural look. The processing, testing, and comparison were done on laptop with Intel Core i7-10510U CPU and of 16 GB RAM. Figures 4 to 7 presents the comparison results. Table 1 offer the assessment scores of the comparison. Figures 8 to 10 present the assessment scores as charts.

Figure 3 offer the results of applying the origin Fuzzy-II algorithm and the proposed algorithm to a set of real low-contrast satellite images. the low-contrast satellite images show a fog-like appearance and lack of detail. The images result from applying the origin Fuzzy-II algorithm had insufficient contrast, it tends to over-brightens the image, especially in highly illuminated areas. which lead to loss image information and made the colors look faded. While the images produced by the proposed algorithm are characterized by natural contrast, sufficient brightness, appropriate colors, and free from any visual distortions. This is essential in computer vision applications because these results are achieved through a fast and computationally uncomplicated algorithm.

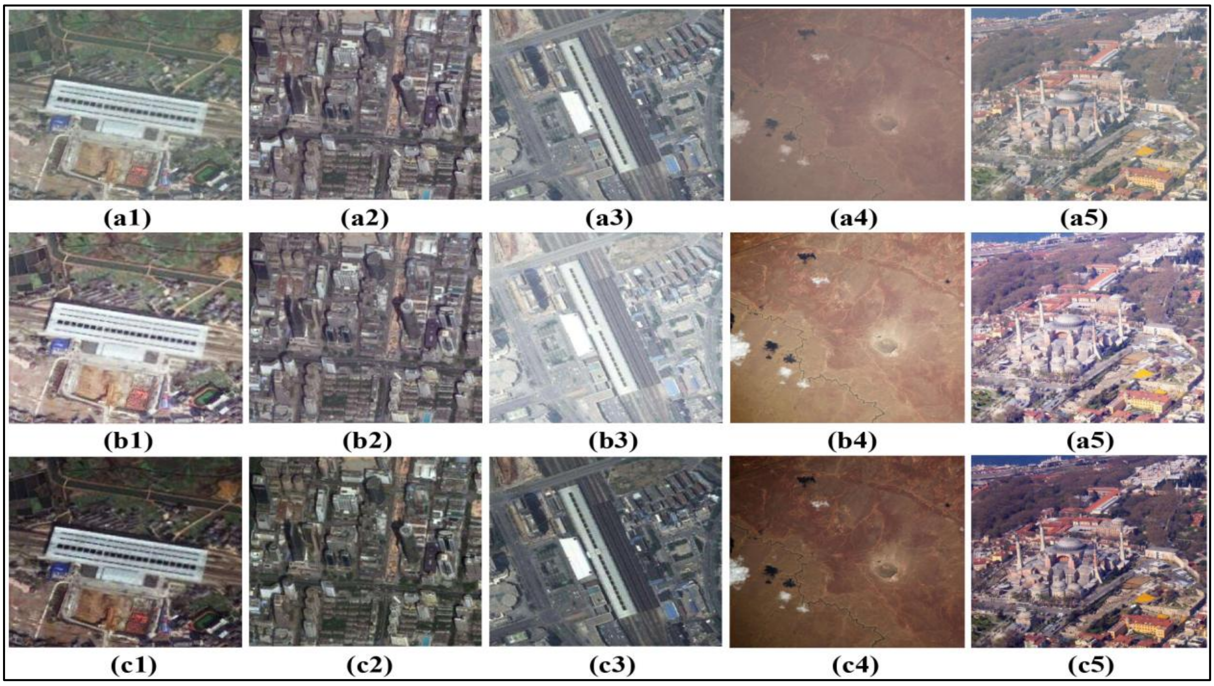

Figure 3 The outcomes of applying the origin Fuzzy-II and the proposed algorithms to a set of low contrast Satellite Images from Kaggle dataset. (a1-a5) low contrast images, (b1-b5) enhanced images using the origin Fuzzy-II, (c1-c5) enhanced images using the proposed algorithm with δ= 1.9, 1.5, 0.2, 0.8, 4.2 respectively.

Figures 4 to 7, Table 1, and Figures 8 to 10 presents the comparison outcomes. varied results were obtained from applying comparison methods because they use different techniques in processing image contrast. The origin Fuzzy-II algorithm slightly improved the contrast and increased the overall brightness of the image, which affected its colors, as it had lighter colors. This is why it obtained an average value in BRISQUE and above average in NSS. It also obtained an average value in

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processing speed compared to other methods. The ACO-SA-GA method provide acceptable contrast but significantly amplified the brightness in well-lit areas, and the resulting images were oversaturated, resulting in unnatural-looking colors. It performed worst on both BRISQUE and NSS. And was also the slowest to process.

As for AGCWD method, it was the fastest at processing image contrast. However, it produced unnatural contrast with washed-out colors and increase overall brightness, resulting in an average and above average in NSS and BRISQUE respectively. The FCCE method slow to process and it produced images with dark colors, unnatural contrast, and unrealistic brightness. It gets a low value in BRISQUE and below average in NSS.

As for the SSR method, its performance is not good, as it produced unsuitable contrast, pale colors, and darkened some areas of the image. It gets a below average value in BRISQUE, low in NSS, and ranked the fifth in processing time. The SMIPC method achieved a slight improvement in contrast and sharpness and maintained image brightness. It gets high values in both BRISQUE and NSS. It ranks the second in processing speed.

The proposed algorithm produced high-quality images with good contrast and natural colors while maintaining brightness. In addition, there is no distortions or errors were observed in the resulting images. it gets the best values in both BRISQUE and NSS. In terms of processing speed, it ranked the fourth with an average of (0.196) second. Despite that, the limitation of the proposed algorithm is not fully automated, that it needs to user-configuration of (δ) value to produce a high-quality image. However, achieving these satisfactory results within a relatively fast processing time is a good thing, especially since the steps that were modified on the origin Fuzzy-II algorithm are simple, but they increased its ability to process the images.

Regarding the measurement of the complexity of the methods used in the comparison, the complexity measuring approach proposed by J. Schnitzer et al. in 2026 [26] was used in this study. These researchers suggested a practical measure based on the actual performance of the method during the execution. It relies on two key factors: the run-time (in seconds) and the memory usage (in megabytes). Table 1 and Figure 11 presents the run-time and the memory usage (MU) values for each processed image in each method, in addition to the complexity score value for each method. Although the AGCWD method was the least complex in the comparison, the resulting images were not up to par. The SMIPC method was also the second least complex, but it provided little improvement to the images it processed. The proposed algorithm was the third least complex (1.0150), and thus less complex than the origin Fuzzy-II, which was the fourth in the sequence (1.0581). this indicates that the changes made to the origin Fuzzy-II were indeed simple and yielded significantly better results. This is an important principle in developing existing algorithms to make them less complex and produce better results.

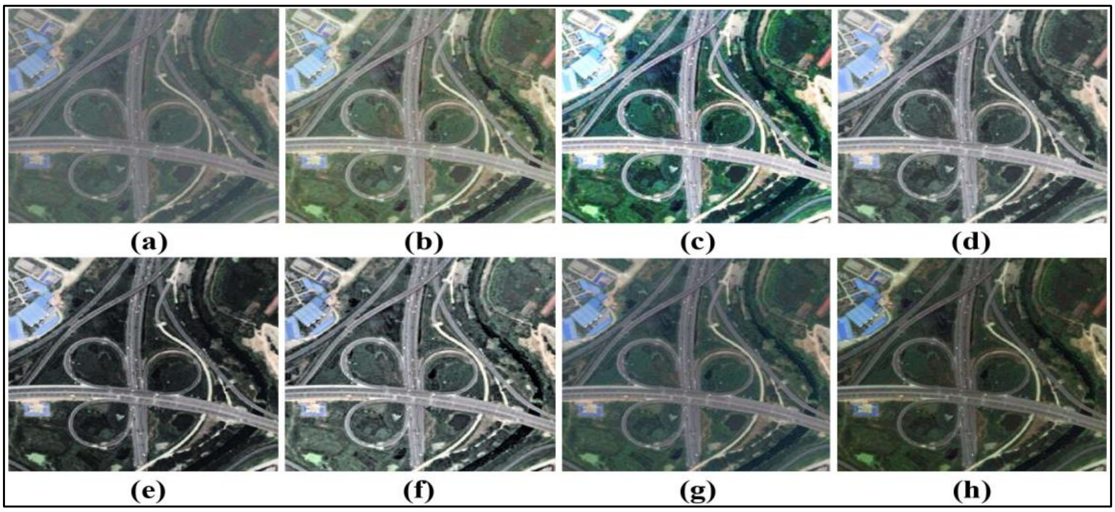

Figure 4 The comparison outcomes of kaggle dataset (Set1): (a) degraded image, (b) Origin Fuzzy-II, (c) ACO-SA-GA, (d) AGCWD, (e) FCCE, (f) SSR, (g) SMIPC, (h) proposed algorithm.

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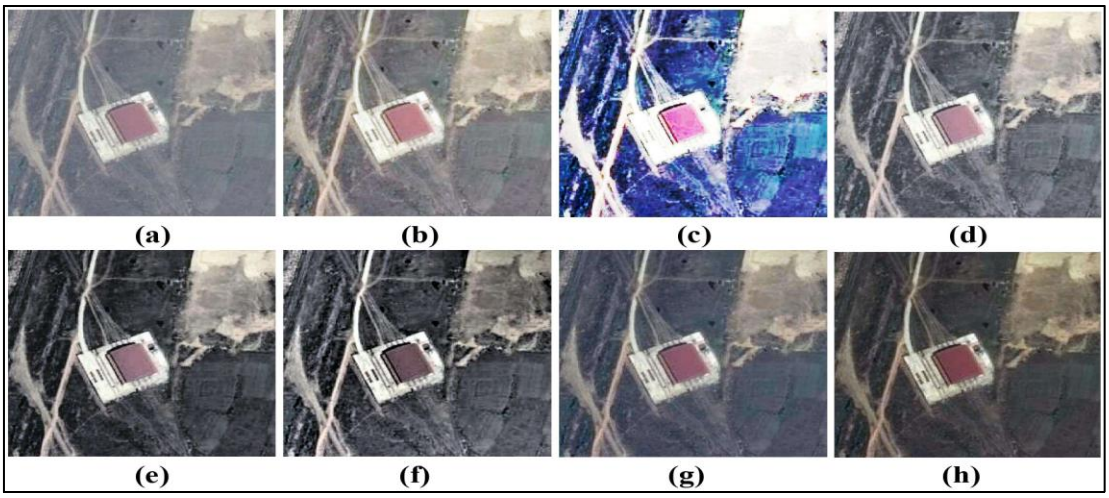

Figure 5 The comparison outcomes of Kaggle dataset (Set2): (a) degraded image, (b) Origin Fuzzy-II, (c) ACO-SA-GA, (d) AGCWD, (e) FCCE, (f) SSR, (g) SMIPC, (h) proposed algorithm.

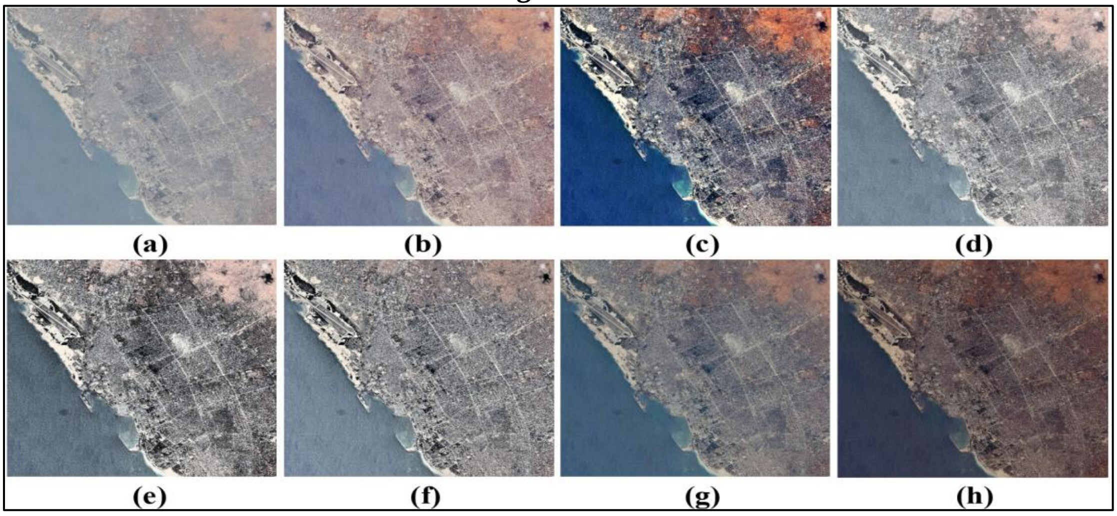

Figure 6 The Comparison outcomes of Kaggle dataset (Set3): (a) degraded image, (b) Origin Fuzzy-II, (c) ACO-SA-GA, (d) AGCWD, (e) FCCE, (f) SSR, (g) SMIPC, (h) proposed algorithm.

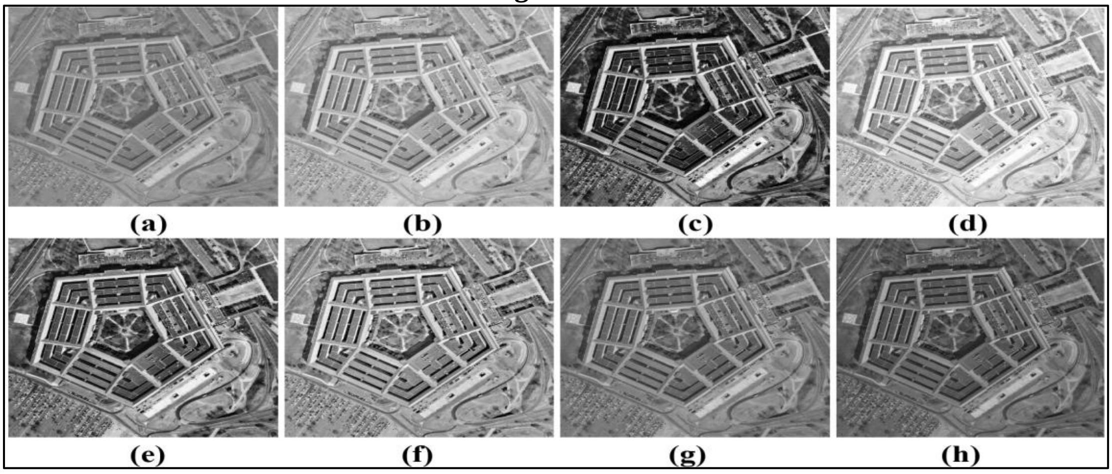

Figure 7 The Comparison outcomes of Kaggle dataset (Set4): (a) degraded image, (b) Origin Fuzzy-II, (c) ACO-SA-GA, (d) AGCWD, (e) FCCE, (f) SSR, (g) SMIPC, (h) proposed algorithm.

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Table 1 The recorded scores for comparison

Methods	Fig	BRISQUE	NSS	Run-Time	MU (MB)	Complexity
Origin Fuzzy-II	4	49.002	2.832	0.135	18.758	1.0581
	5	43.369	2.322	0.109	18.799	
	6	44.851	2.571	0.540	102.938	
	7	48.329	2.567	0.078	13.207	
	Average	46.388	2.573	0.216	38.425	
ACO-SA-GA	4	52.896	2.043	12.053	79.777	3.9770
	5	52.491	2.062	11.103	81.426	
	6	53.320	2.114	19.795	531.127	
	7	53.920	2.146	8.818	187.570	
	Average	53.157	2.091	12.942	219.975	
AGCWD	4	40.650	2.495	0.121	7.352	0.0024
	5	37.935	2.263	0.072	8.355	
	6	42.111	2.406	0.250	12.906	
	7	43.894	2.567	0.038	4.879	
	Average	41.148	2.433	0.120	8.373	
FCCE	4	52.630	2.245	0.225	17.555	1.2892
	5	50.077	2.056	0.218	17.986	
	6	52.992	2.441	0.780	57.938	
	7	53.027	2.706	0.515	27.949	
	Average	52.181	2.362	0.434	30.357	
SSR	4	49.950	2.062	0.314	16.966	1.2848
	5	48.664	2.177	0.274	17.686	
	6	52.164	2.184	0.633	64.751	
	7	51.729	2.647	0.402	29.273	
	Average	50.627	2.268	0.406	32.169	
SMIPC	4	32.047	3.132	0.102	18.778	0.9179
	5	29.884	2.408	0.078	18.981	
	6	35.945	2.732	0.387	103.000	
	7	42.425	2.703	0.072	16.008	
	Average	35.075	2.744	0.160	39.192	
Proposed	4	21.237	3.468	0.132	18.258	1.0150
	5	18.359	2.908	0.083	18.758	
	6	21.516	3.938	0.446	103.000	
	7	22.516	3.552	0.124	15.375	
	Average	20.907	3.467	0.196	38.848	

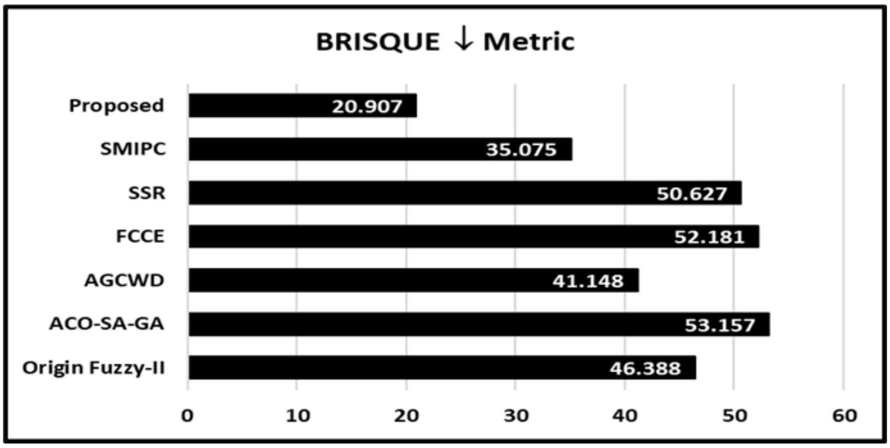

Figure 8 The average BRISQUE scores as chart

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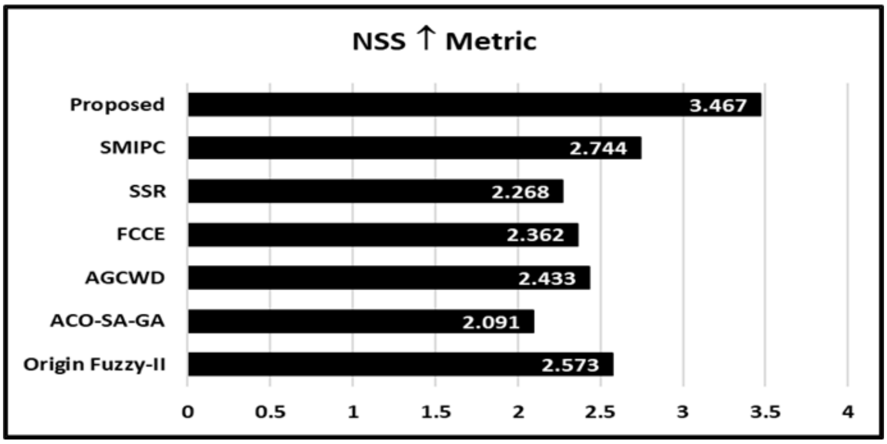

Figure 9 The average NSS scores as chart

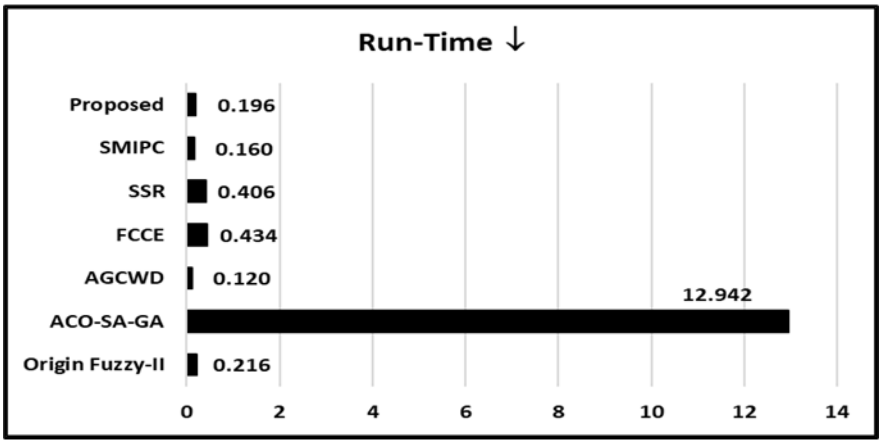

Figure 10 The average run-time as chart

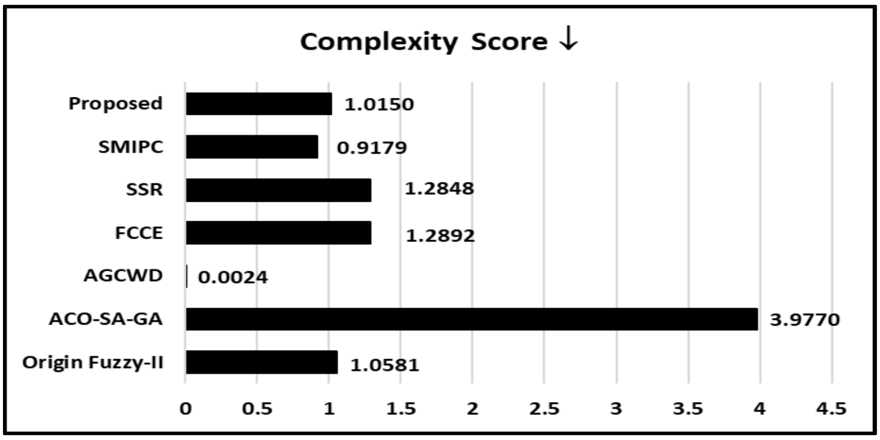

Figure 11 The complexity scores for comparison as chart

5 Conclusion

An amended type-II fuzzy set algorithm is introduced to improve the contrast of satellite images. The proposed algorithm uses a modified Hamacher t-conorm with new lower and upper ranges. The output from this step, in turn, undergoes further processing using sigmoid function method and contrast stretch method to produce the final improved image. The proposed algorithm's performance was tested with natural low-contrast satellite images, compared with six other methods, and the evaluation of the comparison's outcomes was done using two metrics in addition to the processing time. The experimental results obtained from practical experiments and comparisons showed the outstanding performance of the proposed algorithm over other methods, as it produced images with

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sufficient brightness, clear details and natural colors without produce any unwanted artifacts. These results confirm the effectiveness of the proposed contrast enhancement strategy on satellite imagery, which could be useful in many practical applications, including remote sensing, satellite image analysis, environmental monitoring, and drone-based imaging systems, where accurate visual interpretation is critical. Despite its effectiveness, it still relies on manual adjustment of the brightness parameter, which limits its applicability to highly diverse datasets. Therefore, the future work will focus on further developing this algorithm by employed a machine learning method for automatically estimated the brightness parameter (δ) based on the statistical characteristics of the image.

References

[1] K. Sarkar, T. K. Halder, and A. Mandal, "*Adaptive Power-Law and CDF based Geometric Transformation for Low Contrast Image Enhancement*," Multimed. Tools Appl., Vol. 80, No. 4, pp. 6329–6353, Feb. 2021, DOI: 10.1007/s11042-020-10004-6.

[2] N. Sharma and O. P. Verma, "*A Novel Fuzzy based Satellite Image Enhancement*," in Proceedings of International Conference on Computer Vision and Image Processing: CVIP 2016, Volume 2, Singapore: Springer Singapore, 2016, pp. 421–428. DOI: 10.1007/978-981-10-2107-7_38.

[3] B. D. Jadhav and P. M. Patil, "*An Effective Method for Satellite Image Enhancement*," in International Conference on Computing, Communication & Automation, IEEE, May 2015, pp. 1171–1175. DOI: 10.1109/CCAA.2015.7148553.

[4] P. B. Mini and P. Amudha Bhomini, "*A Study in Enhancement of Satellite Images*," Eng. Appl. Artif. Intell., Vol. 138, p. 109259, Dec. 2024, DOI: 10.1016/j.engappai.2024.109259.

[5] V. P. Lalitha, S. Rangaswamy, C. R. Gouthami, T. Jai Balaj, P. Kumar, and R. G. Dolli, "*Satellite Image Enhancement using Neural Networks*," in 2018 3rd International Conference on Inventive Computation Technologies (ICICT), IEEE, Nov. 2018, pp. 211–215. DOI: 10.1109/ICICT43934.2018.9034421.

[6] S. Sulochana and R. Vidhya, "*Satellite Image Contrast Enhancement using Multiwavelets and Singular Value Decomposition (SVD)*," Int. J. Comput. Appl., Vol. 35, No. 7, pp. 1–5, 2011.

[7] R. Aedla, G. S. Dwarakish, and D. V. Reddy, "*Satellite Image Contrast Enhancement Algorithm based on Plateau Histogram Equalization*," in 2014 IEEE Region 10 Symposium, IEEE, Apr. 2014, pp. 213–218. DOI: 10.1109/TENCONSpring.2014.6863028.

[8] D. M. Bongulwar, "*Satellite Image Enhancement*," Int. J. Appl. or I nnovation Eng. M anagement, Vol. 6, No. 6, pp. 145–149, 2017.

[9] Z. Huang et al., "*Optical Remote Sensing Image Enhancement with Weak Structure Preservation via Spatially Adaptive Gamma Correction*," Infrared Phys. Technol., Vol. 94, pp. 38–47, Nov. 2018, DOI: 10.1016/j.infrared.2018.08.019.

[10] T. Trongtirakul, W. Chiracharit, S. Imberman, and S. Agaian, "*Fractional Contrast Stretching for Image Enhancement of Aerial and Satellite Images*," J. Imaging SCI. Technol., Vol. 63, No. 6, pp. 060411-1-060411–11, Nov. 2019, DOI: 10.2352/J.ImagingSci.Technol.2019.63.6.060411.

[11] A. Asokan, D. E. Popescu, J. Anitha, and D. J. Hemanth, "*Bat Algorithm based Non-linear Contrast Stretching for Satellite Image Enhancement,"* Geosciences, Vol. 10, No. 2, p. 78, Feb. 2020, DOI: 10.3390/geosciences10020078.

[12] N. T. Trung, X.-H. Le, and T. M. Tuan, "*Enhancing Contrast of Dark Satellite Images based on Fuzzy Semi-Supervised Clustering and an Enhancement Operator*," Remote Sens., Vol. 15, No. 6, p. 1645, Mar. 2023, DOI: 10.3390/rs15061645.

[13] Z. Saberi, N. Hashim, A. Ali, P. Boursier, J. Abdullah, and Z. E. Che, "*Adaptive Contrast Enhancement of Satellite Images based on Histogram and Non-linear Transfer Function Methods*," Int. J. Appl. Math., Vol. 53, No. 1, p. 341, 2023.

ISSN:2302-8149
e-ISSN:2540-9719

[14] D. Chinaramanamma and B. Anuradha, "*Image Enhancement of Satellite Images using Contrast Limited Adaptive Histogram Equalization and NLM*," Int. J. SCI. Res. SCI. Technol., Vol. 11, No. 2, pp. 182–188, 2024, DOI: https://doi.org/10.32628/IJSRST52411219.

[15] T. Chaira, "*An Improved Medical Image Enhancement Scheme using Type II fuzzy set*," Appl. Soft Comput., Vol. 25, pp. 293–308, Dec. 2014, DOI: 10.1016/j.asoc.2014.09.004.

[16] Y. Zou, X. Dai, W. Li, and Y. Sun, "*Robust Design Optimisation for Inductive Power Transfer Systems from Topology Collection based on an Evolutionary Multi-Objective Algorithm*," IET Power Electron., Vol. 8, No. 9, pp. 1767–1776, Sep. 2015, DOI: 10.1049/iet-pel.2014.0468.

[17] A. A. Jafari, S. Tahmasebi, and M. Alizadeh, "*The Beta-Gompertz Distribution*," Rev. Colomb. Estadística, Vol. 37, No. 1, p. 141, Jul. 2014, DOI: 10.15446/rce.v37n1.44363.

[18] S. Park, Y.-G. Shin, and S.-J. Ko, "*Contrast Enhancement using Sensitivity Model-based Sigmoid Function*," IEEE Access, Vol. 7, pp. 161573–161583, 2019, DOI: 10.1109/ACCESS.2019.2951583.

[19] P. Hoseini and M. G. Shayesteh, "*Efficient Contrast Enhancement of Images using Hybrid Ant Colony Optimisation, Genetic Algorithm, and Simulated Annealing*," Digit. Signal Process., Vol. 23, No. 3, pp. 879–893, May 2013, DOI: 10.1016/j.dsp.2012.12.011.

[20] S. C. Huang, F. C. Cheng, and Y. S. Chiu, "*Efficient Contrast Enhancement using Adaptive Gamma Correction with Weighting Distribution*," IEEE Trans. Image Process., Vol. 22, No. 3, pp. 1032–1041, 2013, DOI: 10.1109/TIP.2012.2226047.

[21] A. S. Parihar, O. P. Verma, and C. Khanna, "*Fuzzy-Contextual Contrast Enhancement*," IEEE Trans. Image Process., Vol. 26, No. 4, pp. 1810–1819, Apr. 2017, DOI: 10.1109/TIP.2017.2665975.

[22] D. J. Jobson, Z. Rahman, and G. A. Woodell, "*Properties and Performance of a Center/Surround Retinex*," IEEE Trans. Image Process., Vol. 6, No. 3, pp. 451–462, Mar. 1997, DOI: 10.1109/83.557356.

[23] Z. Al-Ameen, "*Contrast Enhancement of Medical Images using Statistical Methods with Image Processing Concepts*," in 2020 6th International Engineering Conference "Sustainable Technology and Development" (IEC), IEEE, Feb. 2020, pp. 169–173. DOI: 10.1109/IEC49899.2020.9122925.

[24] A. Mittal, A. K. Moorthy, and A. C. Bovik, "*No-Reference Image Quality Assessment in the Spatial Domain*," IEEE Trans. Image Process., Vol. 21, No. 12, pp. 4695–4708, Dec. 2012, DOI: 10.1109/TIP.2012.2214050.

[25] Y. Fang, K. Ma, Z. Wang, W. Lin, Z. Fang, and G. Zhai, "*No-Reference Quality Assessment of Contrast-Distorted Images based on Natural Scene Statistics*," IEEE Signal Process. Lett., Vol. 22, No. 7, pp. 838–842, 2015, DOI: 10.1109/LSP.2014.2372333.

[26] J. Schnitzer, Z. Al-Ameen, and B. Mahmood, "*Measuring the Complexity of Image Enhancement and Restoration Algorithms using a Logarithmic Model*," Electron. Imaging, Vol. 38, No. 3, pp. 319-1-319–7, Mar. 2026, DOI: 10.2352/EI.2026.38.3.MOBMU-319.