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Improved Fuzzy-associated Memory Techniques for Image Recovery

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Abstract

This paper introduces an improved fuzzy association memory (IFAM), an advanced FAM method based on the T-conorm probability operator. Specifically, the T-conorm probability operator fuzzifies the input data and performs fuzzy logic operations, effectively handling ambiguity and uncertainty during image restoration, which enhances the accuracy and effectiveness of the restoration results. Experimental results validate the performance of IFAM by comparing it with existing fuzzy association memory techniques. The root mean square error shows that the restoration rate of IFAM reached 80%, compared to only 40% for the traditional fuzzy association memory technique.

Index Terms: Fuzzy association memory, Image processing, Image restoration, Root means square error, Triangular conorm probability operator

I. INTRODUCTION

With the development of artificial intelligence, image processing has been widely applied in various fields such as healthcare, military, security, industrial inspection, and remote sensing [1-4]. Image processing involves several steps, including image restoration, segmentation, and recognition [5-7]. Image restoration is a long-standing low-level vision problem that aims to restore high-quality images from low-quality ones (e.g., downscaled, noisy, and compressed images) [8].

Image restoration is a widely studied problem in computational imaging [9-11]. This process aims to recover and reconstruct low-quality distorted or corrupted images based on known information and algorithms and obtain results close to the original image [12-13]. However, this is an ill-posed problem within the sphere of image processing, stemming from its high demand in broad intelligent applications scenarios, particularly in mobile image editing [14]. The restoration process is traditionally regularized by constraining the solutions to be consistent with prior knowledge regarding the image [15]. Standard image restoration algorithms include interpolation-based methods, variational-based methods, sparse representation-based methods, and neural network-based methods.

Compared with these standard restoration algorithms, the fuzzy association memory (FAM) technique can handle various types of image degradation problems and noise, including additive noise, salt-and-pepper noise, and Gaussian noise. Although current FAM approaches exhibit high efficiency in restoring different objects within the same background, they suffer from low efficiency in restoring the same objects within the same background. In addition, they suffer from restoration failures in similar cases, leading to a loss of image details. Based on these deficiencies, this study proposes an improved FAM (IFAM) method based on the T-

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operator (also known as the probability operator) introduced by Goguen et al. [16] to enhance the ability of the FAM to restore images with the same background.

The proposed image restoration process is divided into three main steps:

1. Image pre-processing facilitates subsequent image processing operations by applying gray scaling.
2. The IFAM algorithm is applied to denoise the image and restore its original presentation.
3. The quality of the restored image was evaluated using the root mean square error (RMSE) metric, with smaller values indicating higher image restoration quality.

II. T-CONORM OPERATOR OF FUZZY ASSOCIATIVE MEMORY

A. Fuzzy Associative Memory

Memory is a three-stage system: (1) recording, which stores information; (2) storage, which holds information stably; and (3) recall, which retrieves the stored information [17]. Psychological research has revealed that the human brain relies on an association for memory recall, which associates a remembered item with specific information or another item. A FAMNN combines the concepts of fuzzy operations and rules to interpret fuzziness. In 1973, Nakano modeled associative memory [18], and in 1987, Kosko was the first to propose a FAM network [19], whose model structure is illustrated in Fig. 1.

FAM is a fully connected structure formulated as follows:

$$Y = X \odot W \tag{1}$$

where the symbol $\odot$ represents the maximum/minimum operator, W represents the weight value associated with the connection between the input and output nodes, and X and Y represent the input and output patterns, respectively.

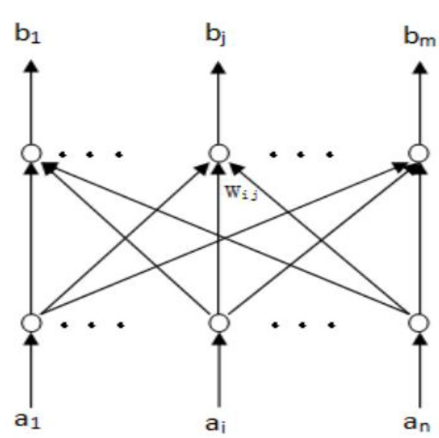

Fig. 1. Fuzzy associative memory neural network (FAMNN)

The weights in the FAM are computed using the input pattern X and transpose of X, as indicated in Eq. (2). Weight computation depends on the fuzzy operations and rules employed in the FAM. The weights capture the relationships and associations between the input and output patterns, enabling the FAM to retrieve or recall an appropriate output pattern based on a given input pattern.

$$W_i = \Sigma_i^n (X_i)^T \wedge X_i \tag{2}$$

In picture recovery using the FAM, the input pattern X is computed through the association process presented in Eq. (3). Similarly, the output pattern Y was calculated using Eq. (4). The computational processes described in Eqs. (3) and (4) are contingent on the specific implementation and rule set employed in the FAM. These equations encapsulate the intricate associations and correlations between the input and output patterns, enabling the FAM to generate reconstructed or recovered images with high fidelity based on the provided input patterns. The adaptable formulas enable nuanced interpretation of fuzzy data, thereby facilitating robust image restoration across various degradation scenarios.

$$Y = X \odot W \tag{3}$$

If and only if $X \geq Y$

$$X = Y \odot W^T \tag{4}$$

If and only if $X \leq Y$

B. T-conorm Operator of Fuzzy Associative Memory

A fundamental concept in FAM is the triangular norm (T-norm), which is a class of binary operations typically denoted by T, whose domain and range are the interval [0,1]. For any $a, b \in [0,1]$, the T-norm $T(a,b)$ satisfies the following properties:

1. Commutativity: $T(a,b) = T(b,a)$
2. Associativity: $T(a,T(b,c))=T(T(a,b),c)$
3. Monotonicity:
   If $a \leq c$ and $b \leq d$, then $T(a,b) \leq T(c,d)$
4. Boundary condition: $T(a,1)= a$

Table 1 lists common triangular moduli.

Table 1. Commonly used triangular modulus formula

Name	Expressions
Take small values	$T_M(x,y) = \min(x,y)$
Multiplication	$T_p(x,y) = x*y$
Lukasiewicz	$T_L(x,y) = \max(x+y-1, 0)$

Definition 1 [20]: A triangular mode T is defined as follows:

1. A T-norm if it satisfies $\forall a \in [0,1]$, $aT1 = a$.
2. A T-conorm (also known as S-norm)
   if it satisfies $\forall a \in [0,1]$, $aT0 = a$.

Table 2. Commonly used trigonometric comodules formulas

Name	Expressions
Take the larger value	$T_M(x,y) = \max(x,y)$
Multiplication	$T_p(x,y) = x+y-x*y$
Lukasiewicz	$T_L(x,y) = \min(x+y,1)$

These definitions provide the mathematical foundation for the intersection (T-norm) and union (T-conorm) operations in fuzzy set theory, which are crucial for implementing the FAM. The choice between T-norm and T-conorm at various stages of the FAM algorithm can significantly influence its behavior and performance in applications such as image restoration. Table 2 lists a few commonly used trigonometric co-modules.

This study applies the T-Conorm operator to the FAM, extending its capabilities in image restoration. T-norm and S-norm (T-conorm) are frequently employed in fuzzy inference systems and fuzzy neural networks [21-22].

The implication operator T for the triangular norms and conorms in this study was established based on the T operator proposed by Goguen [23] and further developed by Bandler et al. [24]. This is formulated as follows:

$$v_{(x,y)} = \begin{cases} T_2(x,y) = x*y \\ T_3(x,y) = x+y-x*y \end{cases} \tag{5}$$

The T-conorm operator-based FAM is referred to as T-con-FAM.

$$Y = X \wedge W^T \tag{6}$$

where X is the input vector, Y is the output vector, W is the weight matrix, T is the fuzzy maximum, and $\wedge$ is the fuzzy minimum operation.

The weight matrix is calculated as follows:

For each i-mode pair $\{(x,y)|i \in R\}$, the weights are calculated based on Eq. (7), and the weight matrix W is obtained by concatenating all the mode pairs i.

$$W = \Sigma_i^n S_v \cup S_v' = \Sigma_i^n S_{v(x,y)} \cup S_{v(x,y)}' \tag{7}$$

where S is the intact image and S' is the damaged image.

The recovered image error rate is evaluated based on the RMSE metric:

$$RMSE = \sqrt{\frac{1}{n}\Sigma_{i=1}^n (p_i - q_i)^2} \tag{8}$$

where p_i and q_i denote the pixel values of the i-th pixel point in the first and second images, respectively, and n denotes the total number of pixel points in the two images.

III. RESULTS

A. Experimental

The experimental setup involved an Intel(R) Core (TM) i7-8700 CPU @ 3.20 GHz 3.19 GHz system with 8GB of RAM. The application was developed using Visual Studio 2022 C# Windows Form.

The effectiveness of the proposed method in addressing various types of noise was verified using twelve images of different styles. These images included a colorless image and two images of human faces; the remaining photos consisted of rich elements of the starry sky and nebulae. Experimental data are presented in Fig. 2.

In practical scenarios, images may contain various types of noise, which can degrade their quality. To validate the effectiveness of the proposed method in handling such scenarios, the application accepts any type of image as input, including both colored and grayscale images. During the experiments, the provided data were intentionally corrupted by different types of noise such as random noise, salt-and-pepper noise, Gaussian noise, and other forms of noise. Fig. 3 highlights the impact of these noise types on the images, demonstrating the need for robust image recovery techniques.

Furthermore, masks were introduced into facial images to verify the effectiveness of the IFAM. Experimental results demonstrate that the proposed method successfully removed

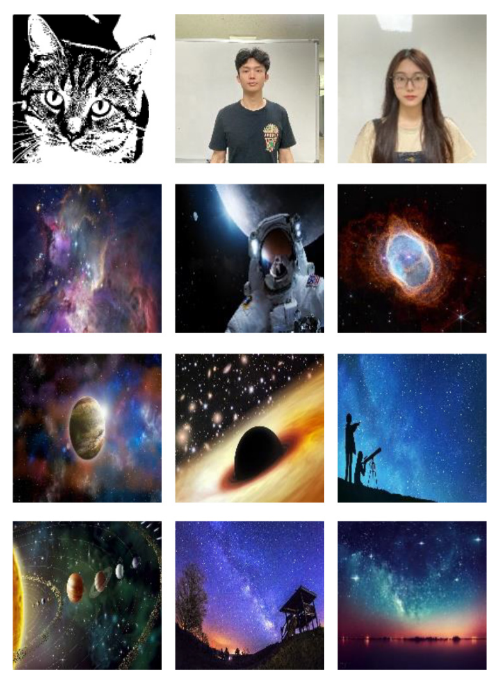

Fig. 2. Experimental data (cont.)

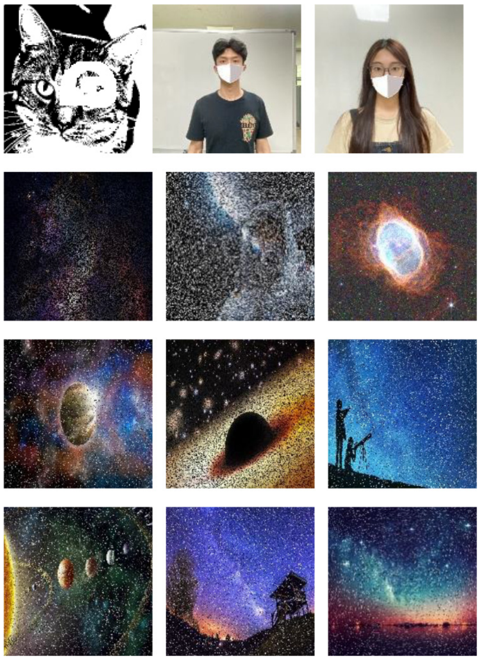

Fig. 3. Image contaminated by noise.

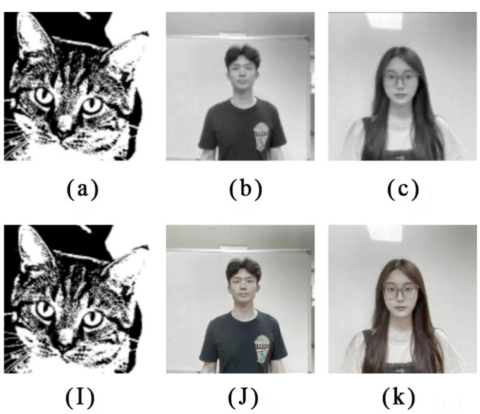

Fig. 4. (a)(b)(c) show the performance of conventional FAM. (I)(J)(K) show IFAM and its improved performance.

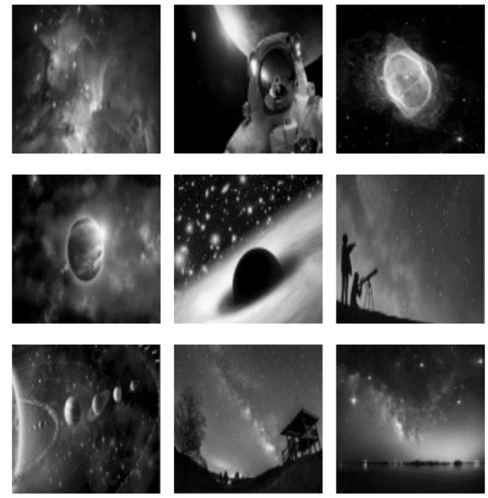

Fig. 5. Conventional FAM

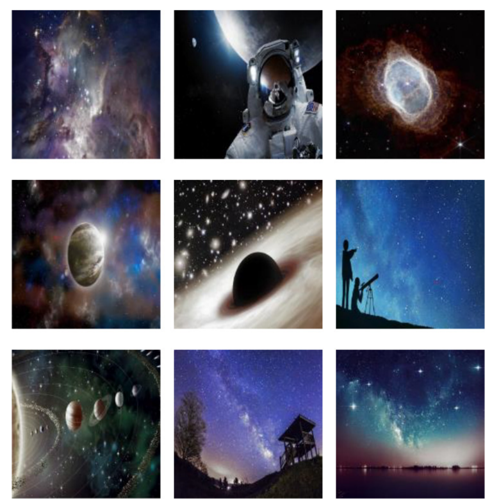

Fig. 6. IFAM

the masks, thereby confirming its effectiveness and accuracy.

Fig. 4 illustrates the experimental results, showing that the traditional FAM performs well in image restoration. However, the proposed IFAM method demonstrates more remarkable results, preserving more image data. Accurately capturing the blurry relationships and intricate correlations between the pixels proves that the IFAM can restore the details and features of the images more precisely.

The following experiments involved starry sky images rich in colorful elements. Fig. 5 shows the experimental results obtained using the traditional and proposed FAM algorithms. Experimental results demonstrate that the traditional FAM method has limitations when dealing with images containing rich color elements and details. While it may achieve satisfactory restoration results in certain simple scenarios, it struggles to effectively restore complex images, particularly those with intricate textures, variations in lighting, and subtle details, such as starry sky images. The IFAM method was employed to restore the same set of images (Fig. 6).

The proposed method incorporates advanced filters and operators, T-conorm operations, and weight calculation strategies to handle images with rich color elements and details effectively. Experimental results demonstrate that the proposed method accurately restores the details and features, producing more realistic, clear, and refined images, thereby exhibiting higher visual quality, efficiency, and restoration effectiveness.

However, color information is lost when converting a color image into a grayscale image, and only the luminance information is retained. A grayscale image uses only grayscale levels to represent the brightness of the image, regardless of color information. Therefore, some details and color variations are lost in a grayscale image compared with a color image.

When restoring grayscale images using the IFAM method, the loss of color information results in an inability to accurately restore the color details of the original image. Although the restored image may approximate the original image in terms of brightness, a lack of color information may prevent complete restoration of the original image details and colors. This highlights the challenges and limitations of information loss during the gray-scaling process, which degrades the quality and accuracy of the overall restored image.

B. Accuracy

Table 3 presents the RMSE obtained from the traditional FAM and the proposed IFAM methods for image processing. These images included both color and grayscale. The results indicate that the IFAM outperforms the traditional FAM method when handling facial images and images with rich elements, such as starry skies. During restoration, the traditional FAM method often fails to accurately capture subtle color variations and texture details, resulting in restored images that lack realism and fineness. Additionally, traditional methods tend to produce blurry or excessively smooth restoration results when dealing with complex backgrounds and intricate noise, causing images to lose their original details and features.

Table 4 reports the best, average, and worst image restoration results. The IFAM method outperforms the conventional FAM method.

Table 3. RMSE values of the traditional and the proposed FAM

RMSE Image	Algorithms	
	Traditional FAM	IFAM
1	11.855	9.527
2	12.593	9.633
3	15.849	6.871
4	18.774	14.849
5	15.261	8.155
6	32.511	27.248
7	53.495	9.133
8	18.271	6.405
9	12.457	5.016
10	0.412	0.412
11	27.529	10.777
12	45.736	16.160

Table 4. Performance Evaluation

RMSE	Conventional FAM	IFAM
Best	0.412	0.412
Avg	20.629	9.918
Worst	53.495	27.248

The proposed IFAM method demonstrated significant advancements over traditional FAM techniques for image restoration. Based on the comprehensive evaluation of full-reference image quality assessment algorithms by Zhang et al. [25], this study defines an RMSE threshold of 18.5 as the criterion for restoration failure. Using this benchmark, the IFAM method achieved an 80% success rate compared to the 40% success rate of the conventional FAM. This improvement is particularly notable in handling color images and high-resolution data, where the traditional FAM often struggles owing to computational limitations and color information loss. Incorporating the T operator enhances the ability of the IFAM to preserve details and reduce computational complexity, enabling the effective restoration of images with various resolutions and noise levels. Although IFAM excels at restoring grayscale details, it may still struggle to fully preserving color information during restoration, resulting in potentially higher RMSE values for some color-rich images. Nevertheless, the broad applicability and improved performance of the method in various scenarios underscores its significance in advancing image restoration techniques. However, careful consideration of image characteristics and restoration requirements remains crucial for optimal results.

IV. DISCUSSION AND CONCLUSIONS

This study explored methods for restoring images with the same background and objects, such as the FAM and T-conorm FAM. The proposed approach, IFAM, is based on the T-conorm FAM, which utilizes fuzzy logic operations to effectively address the relationship between intact and corrupted images. Twelve images with diverse styles were used in the experiments, including a grayscale image, two facial images, and others featuring rich elements, such as starry skies and nebulas. The effectiveness of image restoration was evaluated using the RMSE to determine the restoration success rate.

In addition, the different image samples used in the experiments further validate the generality and applicability of the proposed IFAM method. Whether it was colorless images, facial images, or images with rich sky and nebular elements and achieved satisfactory restoration results.

Experimental results show that the proposed IFAM method successfully restored various noisy images while preserving their fine details. They also demonstrated the robustness of this method in handling multiple types of noise, including random, salt-and-pepper, and Gaussian noise. However, using a grayscale image preprocessing method can degrade the image restoration quality. Grayscale conversion in images with rich color elements can lead to the loss of color information and features, reducing restoration accuracy and increasing RMSE values.

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REFERENCES

[1] D. Shen, G. Wu, and H. I. Suk, "Deep learning in medical image analysis," *Annual review of biomedical engineering*, vol. 19, no. 1, pp. 221-248, Aug. 2017. DOI: 10.1146/annurev-bioeng-071516-044442.
[2] L. Zhang, L. Zhang, and B. Du, "Deep learning for remote sensing data: A technical tutorial on the state of the art," *IEEE Geoscience and remote sensing magazine*, vol. 4, no. 2, pp. 22-40, Jun. 2016. DOI: 10.1109/MGRS.2016.2540798.
[3] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis," *Medical image analysis*, vol. 42, pp. 60-88, Dec. 2017. DOI: 10.1016/j.media.2017.07.005.
[4] V. Wiley and T. Lucas, "Computer vision and image processing: a paper review," *International Journal of Artificial Intelligence Research*, vol. 2, no. 1, pp. 29-36, Jan. 2018. DOI: 10.29099/ijair.v2i1.42.
[5] B. Jähne, "Digital image processing," in *Springer Science & Business Media*, 6th ed. Berlin, DE : Springer, 2005. DOI: 10.1007/3-540-27563-0.
[6] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, May 2015. DOI: 10.1038/nature14539.
[7] Y. Yang and H. Wang, "Multi-view clustering: A survey," *Big data mining and analytics*, vol. 1, no. 2, pp. 83-107, Jun. 2018. DOI: 10.26599/BDMA.2018.9020003.
[8] J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool, and R. Timofte, "Swinir: Image restoration using swin transformer," *in Proceedings of the IEEE/CVF international conference on computer vision*, Online, pp. 1833-1844, 2021.
[9] A. Lucas, M. Iliadis, R. Molina, and A. K. Katsaggelos, "Using deep neural networks for inverse problems in imaging: beyond analytical methods," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 20-36, Jan. 2018. DOI: 10.1109/MSP.2017.2760358.
[10] M. Bertalmío, "Denoising of photographic images and video", *fundamentals, Open challenges and new trends*, Berlin, DE: Springer, 2018. DOI: 10.1007/978-3-319-96029-6.
[11] K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising," *IEEE transactions on image processing*, vol. 26, no. 7, pp. 3142-3155, Jul, 2017. DOI: 10.1109/TIP.2017.2662206.
[12] A. Lucas, M. Iliadis, R. Molina, and A. K. Katsaggelos, "Using deep neural networks for inverse problems in imaging: beyond analytical methods," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 20-36, Jan. 2018. DOI: 10.1109/MSP.2017.2760358.
[13] M. T. McCann, K. H. Jin, and M. Unser, "Convolutional neural networks for inverse problems in imaging: A review," *IEEE Signal Processing Magazine*, vol. 34, no. 6, pp. 85-95, Nov. 2017. DOI: 10.1109/MSP.2017.2739299.
[14] X. Jin, Z. Wu, Z. Hou, H. Peng, and Y. Zhang, "Dual prior learning for blind and blended image restoration," *IEEE Transactions on Image Processing*, vol. 31, pp. 1042-1056, Jan. 2021. DOI: 10.1109/TIP.2021.3135482.
[15] J. Liu, Y. Sun, X. Xu, and U. S. Kamilov, "Image restoration using total variation regularized deep image prior," *in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Brighton, GB, pp. 7715-7719, 2019. DOI: 10.1109/ICASSP.2019.8682856.
[16] S. Weber, "A general concept of fuzzy connectives, negations and implications based on t-norms and t-conorms," *Fuzzy sets and systems*, vol. 11, no. 1-3, pp. 115-134, Mar. 1983. DOI: 10.1016/S0165-0114(83)80073-6.
[17] B. Lautrup, L. K. Hansen, I. Law, N. Mørch, C. Svarer, and S. C. Strother, *Neural Networks: Computers with Intuition*, London, GB: World Scientific, 1990.
[18] K. Nakano, "Association-A model of associative memory," *IEEE Transactions on. SMC*, vol. 2, no. 3, pp. 331-338, Jul. 1972. DOI: 10.1109/TSMC.1972.4309133.
[19] B. Kosko, "Fuzzy systems as universal approximators," *IEEE transactions on computers*, vol. 43, no. 11, pp. 1329-1333, Nov. 1994. DOI: 10.1109/12.324566.
[20] H. A. Simon, R. B. Allen, N. J. Belkin, K. M. Ford, A. Newell, J. Pearl, J. M. Prager, and P. Wang, "AI's greatest trends and controversies," *IEEE Intelligent Systems and Their Applications*, vol. 15, no. 1, pp. 8-17, Jan. 2000. DOI: 10.1109/5254.820322.
[21] M. M. Gupta and J. Qi, "Theory of T-norms and fuzzy inference methods," *Fuzzy sets and systems*, vol. 40, no. 3, pp. 431-450, Apr. 1991. DOI: 10.1016/0165-0114(91)90171-L.
[22] R. Mesiar, "A note on moderate growth of t-conorms," *Fuzzy sets and systems*, vol. 122, no. 2, pp. 357-359, Sep. 2001. DOI: 10.1016/S0165-0114(00)00070-1.
[23] S. Weber, "A general concept of fuzzy connectives, negations and implications based on t-norms and t-conorms," *Fuzzy sets and systems*, vol. 11, no. 1-3, pp. 115-134, Mar. 1983. DOI: 10.1016/S0165-0114(83)80073-6.
[24] W. Bandler and L. Kohout, "Fuzzy power sets and fuzzy implication operators," *Fuzzy sets and Systems*, vol. 4, no. 1, pp. 13-30, Jul. 1980. DOI: 10.1016/0165-0114(80)90060-3.
[25] L. Zhang, L. Zhang, X. Mou, and D. Zhang, "A comprehensive evaluation of full reference image quality assessment algorithms," *in 2012 19th IEEE International Conference on Image Processing*, Orlando, USA, pp. 1477-1480, Sep. 2012. DOI: 10.1109/ICIP.2012.6467150.

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