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Detail Enhancement of 3D Animation Images Based on Swarm Intelligence Algorithm

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The absence of image details in the area of 3D animation design and generation causes the expression creation process of animation to be concealed, resulting in unnaturally image animation expressions. However, the traditional progression of 3D animation graphics has the issue of the inferior visual effect of image improvement. Hence, this paper proposes an Improved Particle Swarm Optimization based Image Enhancement Model (IPSO-IEM) to address the challenges of poor image effect and enhancement in conventional 3D image automatic generation. The data are taken from the iCartoon face dataset for 3D animation image enhancement. Firstly, the image can lose significant data when the size is reduced in 3D animation design. Therefore, the image is transformed from the spatial domain to achieve multi resolution. Secondly, Gamma adjustment is a proven method that creates a natural look and conserves the mean brightness of the picture with the choice of optimal gamma value. PSO selects the optimal gamma values and is utilized as a global search approach for the best optimum value and most improved image. In this research, an efficient fitness function is suggested to increase the performance of the PSO algorithm.

Keywords: 3D Animation Images, Image Enhancement, Particle Swarm Optimization, Swarm Intelligence

1. INTRODUCTION

Accelerating the evolution of graphics processing technology is the ever-increasing capacity of modern computers to handle visual information in various representations [1]. One of the most important technologies in graphics processing is creating and animating 3D images and visuals with enhanced effects [2].The animation method has been established over a while, either in 3D objects or 2D objects like stop motions, clay, and gesture graphic [3]. The magic of the web has rendered it a dependable and important platform for many industries, all of which influence viewers' visual attention [4]. The animation should not last a few seconds or consist of more than a handful of frames to capture the audience's attention [5]. The purpose of 3D animation software development is to create images in 3D on a computer, and improving the realistic impact of these images requires the realistic and sensitive reproduction of illumination and environment range[6]. Traditional animations are often made frame by frame in hand-drawn animation, while 2D animation makes it difficult to create extended films with detailed imagery. The frames need to be redrawn every time using the 2D method [7]. It is generally accepted that animations will seem smooth at a pace of 60 frames per second [8]. 2D animation objects possess only width and height characteristics [9]. Typography, cartography, technical drawing, advertising, etc., are just a few examples of applications built on conventional printing and drawing technologies that rely heavily on 2D computer graphics [10].

Image processing comprises restoration, enhancement, and extraction, respectively. 3D animation image enhancement consists of modifying some actual image characteristics, like noise removal and sharpness, so that the resulting

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image can be utilized in specific animation applications [11]. In addition, gray-level transformation techniques are often utilized to enhance image contrast, like histogram equalization and gamma correction [12].Several evolutionary algorithms, like PSO and Genetic Algorithm (GA), have recently been united with image enhancement techniques to achieve the desired quality in the enhanced image [13]. Such an evolutionary algorithm finds the optimal intensity variables by increasing the fitness (objectives) functions in the image enhancement progression [14]. The enhancement approaches are generally separated into frequency and spatial domain methods [15]. In spatial domain methods, image pixels are improved directly. Then, the pixel values are altered to obtain the desired enhancements [16]. The non-linear and non-continuous optimization issues may be solved using PSO, a cutting-edge heuristic approach [17]. It is a stochastic optimization method for continuous non-linear functions based on a population [18]. PSO with an objective function that looks at the image's entropy and the number of edges to evaluate image enhancement [19].It has been widely used to improve images because it only needs a few individuals, converges quickly in the early stages of evolution, is easy to use, and is simple to set up [20].

2. RELATED WORKS

Yurui Ren et al. [21] suggested the Global-Flow Local-Attention Framework (GFLAF) for Pose-Guided Person picture Animation and Generation. Generating and animating people in certain positions is the goal of pose-guided picture generation and processing. These tasks demand spatial manipulation of the original information. The global flow fields among source and target are initially estimated within this framework. After that, local attention factors that consider the context of the original source are sampled to provide a realistic depiction of those materials. The experimental outcomes of the image animation and generation tasks show the model's superiority.

Qinchen Cao et al. [22] proposed the Deep Learning-based Classification Model (DLCM) for Polar Feelings of Moe-Style Animation Images.First, the author detects the cartoon characters' facial expressions and extracts the scene and face aspects of the animation images based on this drawing style's expression feature. The author then changes the expressions of the images produced by expression recognition to match the characteristics of the scenes in which they were taken. As a result, the author can soon access the image's extreme emotional states. Finally, the author created a database and performed verification experiments, reaching 81.9% test accuracy.

Huasong Chen et al. [23] recommended the L0 Regularized Cartoon-Texture Decomposition (L0RC-TDC) for repairing imageries degraded by impulse noise and blur. To characterize the cartoon quality and the texture of pictures, the author offers an L0 regularised framelets-based sparse depiction and an L0 regularised DCT-driven sparse estimation. The technique does not rely on local features as most other animation-texture decomposition-based restoration techniques, yet it globally control the crucial non-zero elements of the animation and textures in the DCT and framelets domains. Numerical outcomes demonstrate that the suggested model is superior at deblurring and removing impulsive noise compared to other approaches.

Hao Su and Weina Fu [24] discussed the Statistical Shape Priors (SSP) for the edge texture element of the film and visual 3D animation image enhancement. The animation is first processed employing segmentation, de-noising, and edge detection; next, the statistical shape prior approach wasutilized to improve the edge texture data. The experimental findings demonstrate the superior edge detail information obtained by the suggested strategy. This methodology aids in developing the film and television animation industry by laying a foundation for further research into the field, with the ultimate goal of raising the standard for film and 3D animation excellence.

Kuldip Acharya and Dibyendu Ghoshal [25] deliberated on the Central Moment and Multinomial-based Sub Image Clipped Histogram Equalizations (CM-M-SICHE) for Animation Image Improvement. Multinomial curvature fitting is used in the image histogram to decrease the sum of squared residuals, decreasing the number of pixels for every intensity values. To further improve the calculated data, resampling was used. CM processing on the resampled data values determines the histogram clipping threshold, limiting the over-enhancement ratio. The histogram was split along the middle into two parts. The suggested technique outperforms both quantitative and qualitative performance assessment, as shown by simulation results in Matlab.

Cheng Di et al. [26] presented the Light Weight Convolutional Neural Network (LW-CNN) for 3D Film and Television Animations. The LW-CNN model uses divisible convolution structures to extract 3D feature points from a human face and suggest more precise features with fewer variables. Before extracting features from images, a model uses a face recognition approach reliant on inverted triangle structures to identify the face frames in the training set. In addition, the Generalized Multiple Maximum Dispersion Difference Criterions (GMMSD) and its accompanying feature extraction method were presented as a solution to the issue that the difference criterion-based feature extraction technique cannot successfully extract the discriminative information. GMMSD has been shown to increase the accuracy of facial recognition by extracting unique identifiers from a person's face.

3. IMPROVED PARTICLE SWARM OPTIMIZATION BASED IMAGE ENHANCEMENT MODEL (IPSO-IEM)

As computer technology has increased, image-processing technology has spread into every part of our lives. People are strongly attached to the concept that entertainment and leisure are important. The image processing technology is mostly used to make special effects for movies, computer games, digital cameras, video playback, digital television, and other forms of entertainment. However, image processing technology is often only used to research and apply

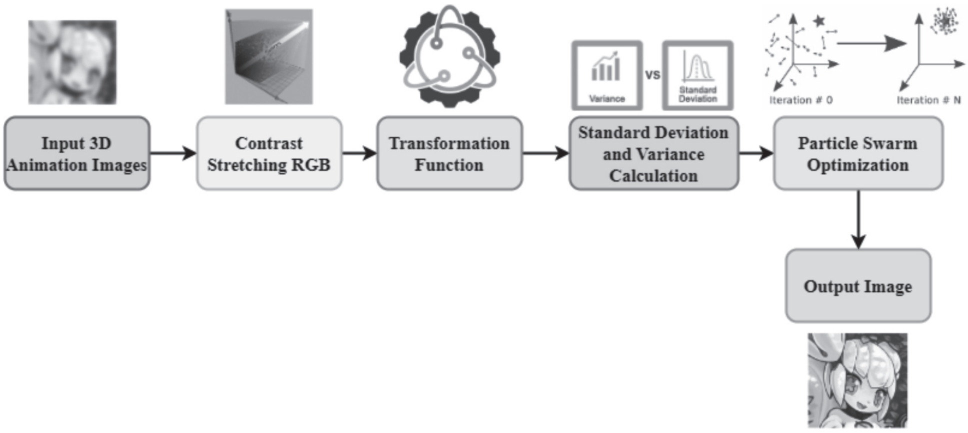

Figure 1 Proposed IPSO-IEM model.

two-dimensional images. Therefore, when the image data is large, it can not fully display the real photos and can not show the details. The emergence of 3D animation technology can better solve the problem that this two-dimensional image can't solve. 3D animation technology will enable people to see graphic images more vividly, concretely, and clearly if applied to image processing technology. Further, the image processing effect is good, the speed is fast, and it has high processing precision.Image enhancement aims to increase the total visual value of images. Both frequency and spatial domain techniques may be used to improve an image.Hence, in this article, the Improved Particle Swarm Optimization based Image Enhancement Model (IPSO-IEM) has been suggested to address the problem of poor image effect and enhancement in conventional 3D image automatic generation. Due to its low complexity, quick convergence, and excellent efficiency, PSO has found widespread practical use. An adaptive technique for improving images is developed following the image's local feature information.

Figure 1 shows the proposed IPSO-IEM model.

3.1 Input 3D Animation Image

The input 3D animation image has been taken from the dataset of [27] for processing the image data.

3.2 Contrast Streching to RGB

Each pixel in the character's animated texture occupies one of the four bytes, and inside each byte are stored the red, green, and blue values for that pixel's color component and the transparency values for that pixel's corresponding pixel point. Animated character data is mapped into the virtual canvas texture through a path across the rendering points, which improves the realism effect. The method of improving 3D animation graphics is outlined, with a skeleton structure based on the concept of the design's content. In digital graphics processing, image enhancement occupies a prominent sector. It's a technique that alters an image's data or information to emphasize an area of interest while downplaying irrelevant details. This is done so that the image best serves the visual response characteristics of the viewer.

3.3 Transformation Function

The local enhancement models use transformation functions based on the gray-level scattering in the vicinity of each pixel in the provided picture. Histogram transformation is regarded as one of the essential procedures for contrast improvement of gray-level pictures, which aids in succeeding higher-level operations like identification and detection.

3.4 Standard Deviation and Variance Calculation

The scale space of the 3D animation is then defined using the color invariance and standard deviations of Gaussian functions, and the Gaussian variance functions of the 3D animation are computed using the image's fixed coefficients.

3.5 PSO Algorithm

The suggested PSO method included edge content, entropy, and standard grey variance into each particle's objective function to properly identify appropriate enhanced images. By imitating the behavior of a bird swarm, the particles in Particle Swarm Optimization (PSO) collaborate to find the best possible solution. As soon as the algorithm was established, it became the focus of many specialists in the field. Its widespread use in 3D animation image enhancement can be attributed to its many benefits, including achieving better results with a smaller sample size, rapid convergence during the early stages of the evolutionary process, simple and direct operation, and streamlined implementation. PSO uses a swarm of particles to interact with one another to discover the best region in a complicated search space.

3.6 Output Image

The PSO's learning factors are updated with each iteration of the proposed algorithm's optimization process. As entropy and gain are an important part of gamma correction, it seems to sense that it would be one of the primary goals in this multi-objective PSO. If entropy gain is considered, the input

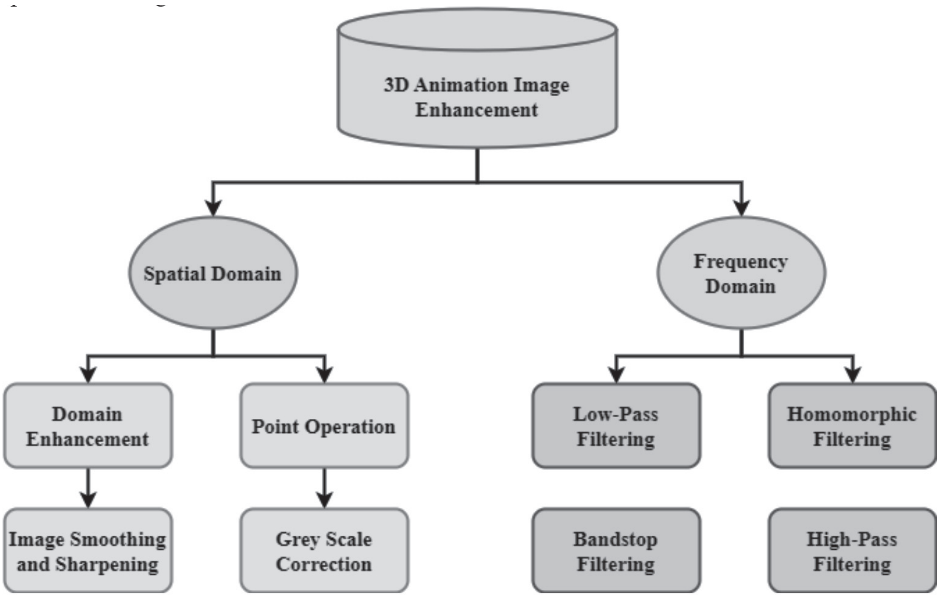

Figure 2 Image Enhancement Model.

image's brightness and contrast may be irreversibly altered or degraded. As a result, many researchers have recently combined PSO with conventional image enhancement techniques.

Animation's visual enhancement process is simulated, the noise problem often appearing in the improved image is investigated, and efficient solutions are offered. The spatial operation of image enhancement is used in the proposed IPSO-IEM model. Improved visual perception of 3D animation is a primary goal of image enhancement, which involves enhancing appropriate image details. In fact, spatial domain processes aim to produce an image with more informative pixel values. Image enhancement, prepared in spatial domains, utilizes a transformation function that creates novel intensities values for every pixel of $N \times M$ actual 3D animation images to produce improved images, where N indicates columns and M represents rows.

$$h(j,i) = T[f(j,i)] \tag{1}$$

As shown in equation (1), where $f(j,i)$ denotes gray values of $(j,\ i)th$ pixel of input images, and $h\ (j,i)$ indicates gray values of the $(j,\ i)th$ pixel of improved images; T denotes transformation functions. The local improvement technique applies the transformation to pixels because of the intensity distribution between the neighboring pixel.

A transformation function is needed to produce novel pixel intensity values from the actual intensity value to enhance image quality to attain enhanced images. In addition, there is a necessity for an assessment function proficient in assessing the quality of output images. Local data was extracted from user-described windows of size $m \times m$. The transformation T is described by:

$$h(j,i) = L(j,i)[f(j,i) - c \times n(j,i)] + n(j,i)^a \tag{2}$$

As inferred from equation (2), a and c are two variables, $n(j,i)$ denotes the local mean of $(j,\ i)th$ pixels of input images over an $m \times m$ windows and $L(j,i)$ indicates improvement functions, which consider both global and local data. The formula for the local mean function is provided in equation (3):

$$n(j,i) = \frac{1}{m \times m} \sum_{y=0}^{m-1} \sum_{x=0}^{m-1} f(y,x) \tag{3}$$

One formula of the enhancement functions $L(j,i)$ utilized in this study is

$$L(j,i) = \frac{l \cdot D}{\rho(j,i) + b} \tag{4}$$

As discussed in equation (4), where l and b denotes two variables, D denotes global mean, and $\rho(i,\ j)$ signifies the local standard deviations of $(j,\ i)$th pixel of input images over an $m \times m$ windows, and is described in equation (5) & (6):

$$D = \frac{1}{N \times M} \sum_{j=0}^{N-1} \sum_{i=0}^{M-1} f(j,i) \tag{5}$$

$$\rho(i,j) = \sqrt{\frac{1}{m \times m} \sum_{y=0}^{m-1} \sum_{x=0}^{m-1} (f(y,x) - n(j,i)^2)} \tag{6}$$

Therefore the transformation functions are expressed as follows:

$$h(j,i) = \frac{l \cdot D}{\rho(j,i) + b}[f(j,i) - c \times n(j,i)] + n(j,i)^a \tag{7}$$

By this transformation (equation (7)),image contrast is stretched because of the local mean as the center of the stretches. In addition, 4 variables are utilized in transformation functions: a, b, c, and l to generate significant variation in processed images.

Figure 2 shows the image enhancement model. Equalizing the animation in 3D feature data utilizing global and local histogram equalization techniques is crucial in improving the animation in 3D feature data. In addition, the mapping function uniquely determines the location of every pixel in output images based on the locations of the corresponding pixels in input images. This is because enhancing the visuals in 3D animation is so crucial. One may essentially categorize image enhancement techniques as frequency or space domain processing. Point operations are typically used to adjust the gray scale range and distribution. A low-pass filter will eliminate the high-frequency component representing the variability and detail, which will blur the image and eliminate the spikes and the variation data around the edge when applied to an image. Standard approaches to image denoising include neighborhood median and averaging filtering. However, after smoothing, the calculation's discrepancy will show more intensely.All sharpening techniques start with a high pass filter. The image is sharpened as the contrast between neighboring regions of similar brightness or darkness increases. The high-frequency details of an image are preserved by a high-pass filter, whereas the low-frequency details are destroyed. A band-stop filter passes most unaltered frequencies, attenuates those in particular ranges to shallow levels, and removes noise.

Choosing criteria associated with a fitness function is necessary for PSO-based image enhancement. A reasonably high intensity of edges in the augmented image is required for the suggested method to work. As a result, an image lacking in natural contrast may get undue credit if fitness criteria are directly related to the number and intensities of the pixel on edge. According to the study's fitness requirement, the image's histogram must be uniform.

The fitness function shown in equation (3) is a good selection for an enhancement measure:

$$F(Z) = \log(\log E(J(Z))) * \frac{m_{edge(J(Z))}}{N * M} * G(J(Z)) \tag{8}$$

As shown in equation (8), where $F(Z)$ denotes the fitness function. $J(Z)$signifies the actual image J with the transformation T employed consistent with equation (1). The variables a, b, c, and l are the corresponding variables provided by particles $Z = (abcl)$. $E(J(Z))$ indicates the intensities of the edge identified with Sobel edge detectors that are employed to transform images $J(Z)$, m edges denote the number of edge pixel discovered with Sobel edge detectors. The Sobel detectors utilized have automatic threshold detectors. N and M are the numbers of pixels in the vertical and horizontal direction of images. $E(J)$ denotes the sum of the intensities of the edge encompassed in the improved picture. Finally, $G(J(Z))$ measures the entropy of images $J(Z)$.

PSO is initialized with groups of the random particle (solution). The PSO algorithm search for optima via a sequence of iteration. The particle's fitness values are assessed on every iteration. The best values of the particle arerealized, and the particle store locations of that values as $pbest$ (particle best). The locations of the best fitness values attained by whichever particle through any iteration are stored as $gbest$ (global best). Utilizing$pbest$ and $gbest$, every particle transfers with certain velocities, computed by Equations 9, 10, and 11.

$$\begin{aligned} U_j = \omega U_{j-1} &+ c_1 * rand() * (pbest - pK) \\ &+ c_2 * rand() * (gbest - pK) \end{aligned} \tag{9}$$

$$pK = puK + U_j \tag{10}$$

$$\omega = \frac{1}{iterNum} \tag{11}$$

As shown in the above equations, where U_j denotes the current velocity, U_{j-1} indicates the prior velocity, pK signifies the present location of particles, puK denotes the prior location of particles, $rand$ represents random numbers between (0, 1), c_1 and c_2 are the stochastic or learning factor, and $iterNum$ denotes current iteration numbers.

Figure 3 displays the flow chart of the PSO in 3D animation Image enhancement. Each particle iteration's outcome is tested for fitness, and the iteration that yields the best fit is chosen. Every iteration ends with comparing all individuals to identify the optimum individual value (pbest); the sum of all pbest values from the first action through the present iteration is referred to as the global optimal value (gbest). By a process known as particle iteration, the local optimum value is repeatedly substituted with the global optimal value. Eventually, pbest will replace gbest once it achieves its optimal value. There will be no use for pbest if it is not the current best value. The evaluation function linked with every particle defines the updated direction of the particle, which is connected to whether or not a greater image-enhancing effect may be accomplished. To improve the image quality of a 3D animation, which often has low contrast and blurry details, more information has to be added, and the result of the particle iteration should be evaluated using a set of predetermined criteria. It is the gradient index that may show the variation between individual pixels. A sharper image is achieved by having a large gradient, which creates a more noticeable difference in grayscale at the image's edges. The entropy of an image is a popular metric for evaluating its quality since it measures the amount of data contained within it. Higher entropy values usually indicate a higher quality and more colorful image. In addition, the gamma transformation is used to improve the contrast of images with an uneven grayscale, and the fractional order operator is used to improve the intricate points of facial features.

4. RESULTS AND DISCUSSION

Image enhancement is vital in computer vision tasks and image processing, improving an image's visual quality. This study suggests Particle Swarm Optimization based Image Enhancement Model (IPSO-IEM) for image enhancement in 3D animation generation. The data is taken from the iCartoonFace dataset [27]. The **iCartoonFace** database is a large-scale database that can be used for two tasks: cartoon face detection and image enhancement. iCartoonFace is a large-scale dataset for cartoon face identification that includes a variety of animation styles. The iCartoonFace identification task is measured on the mAP (mean average precision) metric. The iCartoonFace recognition dataset was created as a large-scale, difficult-to-use resource for cartoon

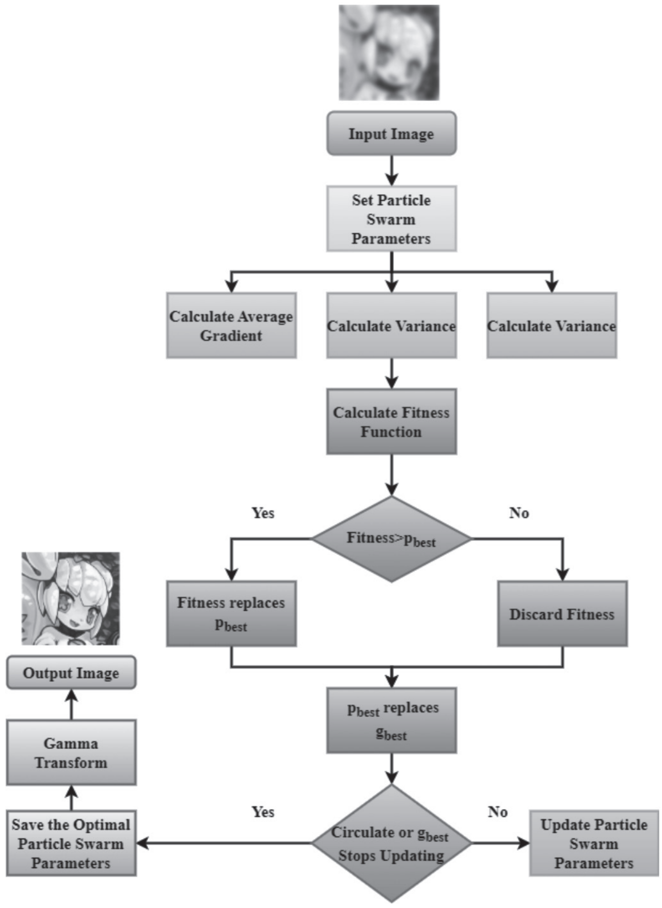

Figure 3 Flow chart of PSO in 3D animation Image enhancement.

face recognition. The graphic offers a visual representation of data from the requested dataset. In the iCartoonFace task, for instance, the algorithm is given a probe image and a gallery of images featuring the same cartoon character, and it must sort the images in the gallery in order of how similar they are to the probe.

4.1 Peak Signal-to-Noise Ratio

This research sheds light on how an IPSO-IEM approach for improving 3D animation images came to be. The suggested method applies local/global transformation functions to improve image quality. Several factors in the transformation function significantly impact its effectiveness. The proposed method first determines the best settings for the mapping function's parameters using PSO and a custom fitness function. The movable parameter is then identified by re-running the mapping function over the updated pixel intensities from the previous step (remapping).Findingsillustrate that the recommended framework outperforms the state-of-the-art methods regarding fitness value, contrast, entropy, edge details, and PSNR. The PSNR ratio is calculated based on equation (1).

Figure 4 demonstrates the PSNR ratio. A PSO-based 3D animation enhancement is provided in this study, which preprocesses the picture utilizing a median filter to eliminate noise and produces better outcomes, and the effectiveness of all these methods is compared on the same dataset. As compared to other approaches, PSO is clearly superior. The noise in the warped 3D images is cleaned up using a non-linear median filter. It does a good task of keeping the input images borders intact

4.2 Structural Similarity Index (SSIM)

PSNR and SSIM are two more objective quantitative metrics used in this research project by our team. The enhancement approaches need to provide PSNR and SSIM values greater than those of the input images compared to their own output. Images with greater PSNR and SSIM values are considered better quality. When these two metrics are considered, it can be said that the quality of the progressed imageries than the original image has been significantly improved thanks to the presented framework. Therefore, a measure that is exceptionally well-suited for use in assessing the effectiveness of an algorithm is provided.

Figure 5 demonstrates the Structural Similarity Index (SSIM).The recommended IPSO-IEM method has a significant advantage over the other improvement strategies when considering all the test pictures. The software is put to the test on several dated, faded color images, and it produces findings that are in line with those provided above. The proposed solution has the potential to support the restoration of an extensive range of cultural artworks from across the world,

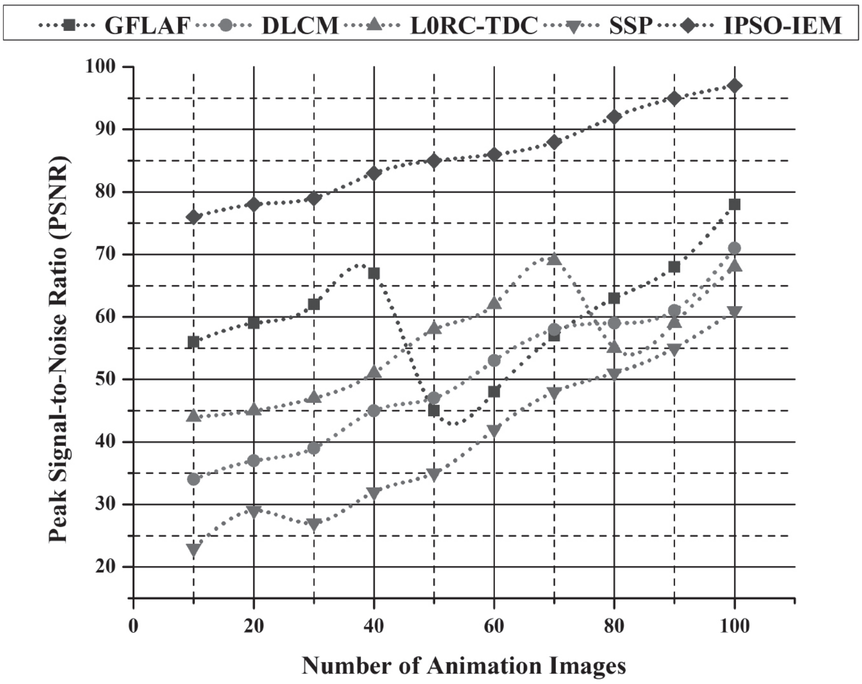

Figure 4 PSNR Ratio.

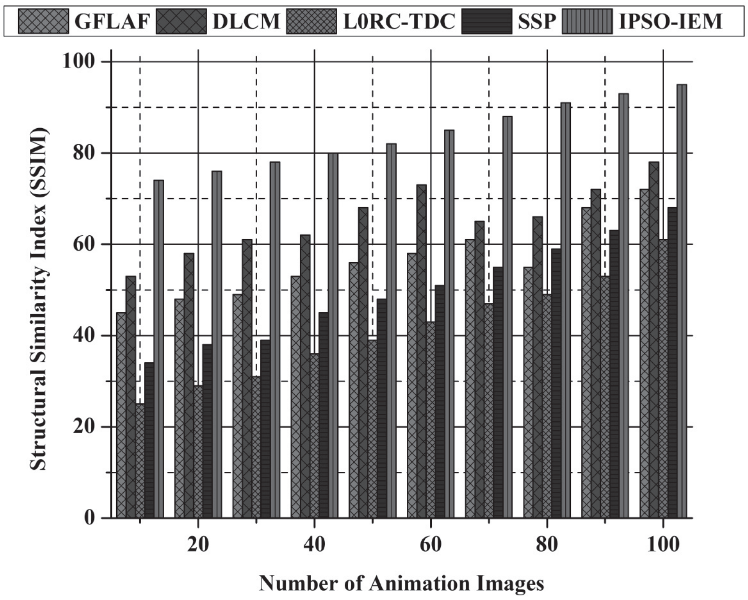

Figure 5 Structural Similarity Index (SSIM).

giving them a fresh lease on digital life in which they will be kept for the foreseeable future.

4.3 Absolute Mean Brightness Errors

It is the complete variance amongst the input and the output picture's mean. The PSNR value of the 3D animation images is measured after being enhanced using various techniques. Greater PSNR values suggest higher contrast enhancement with frequency and phase details preservation and less noise material. When applied to all of the retinal images, our proposed method yields the best PSNR results that can be seen. Other methods cannot produce 3D animation images that have a better PSNR value than those produced by this method. This helps improve the local information as well as the texture details. Parameters such as AMBE are utilized to evaluate the quality of an image based on how well the brightness is preserved. When the AMBE value is lower, the value of brightness preservation is higher. From equation (2), the AMBE has been calculated.

Figure 6 illustrates the absolute mean brightness error. It is measured that the proposed IPSO-IEM model achieves the least AMBE compared to other existing models. It has been discovered that the brightness error between the actual image and the one that outcomes from using this technique

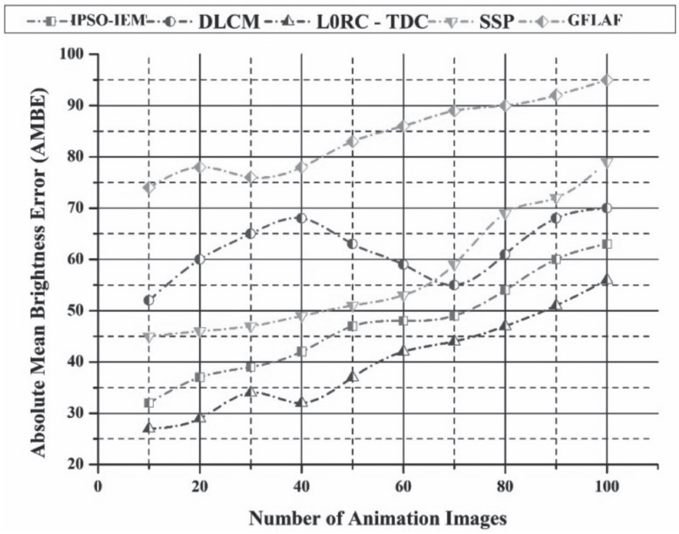

Figure 6 Absolute Mean Brightness Error (AMBE).

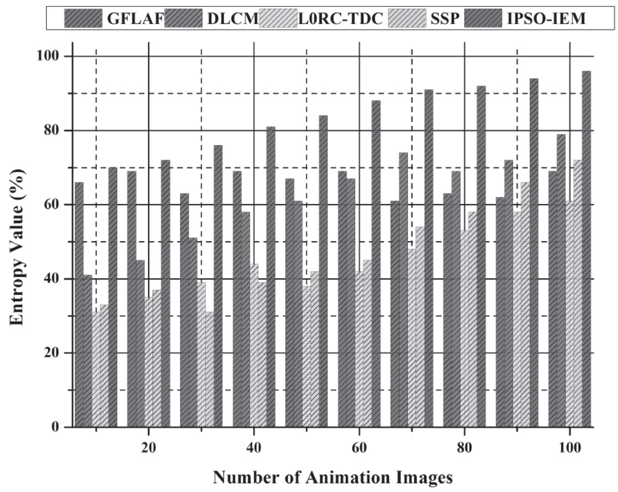

Figure 7 Entropy Value.

are significantly lower than that of other techniques. It is an indication that the proposed method can preserve brightness more effectively.

4.4 Entropy Value

Entropy is a useful statistic for making comparative scientific and technological assessments. An increase in entropy indicates an increase in information density. Furthermore, image histogram uniformization may be achieved by increasing the entropy of the picture. The goal is to maximize the number of edge pixels, edge intensity, and entropy. As a result, the improved image's histogram will have a more normal distribution. Based on equation (8), the entropy value is calculated.

Figure 7 shows the entropy value. The experimental findings show the advantage of the suggested technique in terms of image quality. IPSO-IEM produces a histogram with higher value spacing closely matching the original when applied to an image. This strongly suggests that the suggested approach does not amplify noise. As the PSNR increases together with the reduction of noise amplifying factors superior to those now in use.

5. CONCLUSION

This research presents an IPSO-IEM as a solution to the blur image effect and enhancement in existing methods of automatically generating 3D animation images. The widespread use of this strategy in several facets of 3D image processing has achieved good optimization outcomes. This article proposes a PSO-based method for enhancing color images that do not alter their original hue.To determine the best gamma value and construct a weighted histogram. It is widely accepted that histogram transformation, which includes versions of histogram equalization, constitutes one of the key procedures for contrast improvement of grey-level pictures. An increase in the image's entropy and a more evenly distributed histogram show that its intensities are being used to their fullest potential. The intensity transformation function uses the input image's global and local features, while the objective function reflects the image's entropy and edge structure. Scaling the image is then required to achieve an improved color image, which might cause a gamut issue in isolated areas of the image. After this, filters are applied to the picture to improve it based on the segmentation findings.

REFERENCES

1. Asraf, S. M. H., & Idrus, S. Z. S. (2020, April). Hybrid Animation: Implementation of Two-Dimensional (2D) Animation. In Journal of Physics: Conference Series (Vol. 1529, No. 2, p. 022093). IOP Publishing.
2. Wu, D. Y., Lin, J. H. T., & Bowman, N. D. (2022). Watching VR advertising together: How 3D animated agents influence audience responses and enjoyment to VR advertising. Computers in Human Behavior, 133, 107255.
3. Yang, L. (2021, February). Functionality and artistry in 3d animation scene design. In Journal of Physics: Conference Series (Vol. 1744, No. 4, p. 042212). IOP Publishing.
4. Lian, L., & Lei, T. (2022). Film and Television Animation Sensing and Visual Image by Computer Digital Image Technology. Journal of Mathematics, 2022, 1–8.
5. Wang, Y. (2022). VISUAL REALITY OF DIGITAL 3D ANIMATION BASED ON MENTAL DIMENSION. PsychiatriaDanubina, 34(suppl 5), 418–418.
6. Ye, F. (2021). Application of Photoshop Graphics and Image Processing in the Field of Animation. Journal of Sensors, 2021, 1–18.
7. Wang, X., Wu, C., Yin, S., Ni, M., Wang, J., Li, L., ... & Duan, N. (2023). Learning 3D Photography Videos via Self-supervised Diffusion on Single Images. arXiv preprint arXiv:2302.10781.
8. Pan, C. (2022, April). The application of 3D digital animation in landscape design. In International Conference on Image, Signal Processing, and Pattern Recognition (ISPP 2022) (Vol. 12247, pp. 193–197). SPIE.
9. Inoue, M., Freel, T., Van Avermaete, A., & Leevy, W. M. (2020). Color enhancement strategies for 3D printing of x-ray computed tomography bone data for advanced anatomy teaching models. Applied Sciences, 10(5), 1571.
10. Chen, R., Sulaimani, H. J., & Hoon, K. S. (2022). The modelling and implementation of the virtual 3D animation scene based on the geometric centre-of-mass algorithm. Applied Mathematics and Non-linear Sciences, 7(2), 413–422.
11. Kumar, A., Jilani Saudagar, A. K., AlKhathami, M., Alsamani, B., Abul Hasanat, M. H., Khan, M. B., . . . & Singh, K. U. (2022). AIAVRT: 5.0 Transformation in Medical Education with Next Generation AI-3D Animation and VR Integrated Computer Graphics Imagery. Traitement du Signal, 39(5).
12. Zakir, S., Maiyana, E., Khomarudin, A. N., Novita, R., & Deurama, M. (2021, February). Development of 3D Animation Based Hydrocarbon Learning Media. In Journal of Physics: Conference Series (Vol. 1779, No. 1, p. 012008). IOP Publishing.
13. Hu, T., Liang, C., Min, G., Li, K., & Xiao, C. (2020). Generating video animation from single still image in social media based on intelligent computing. Journal of Visual Communication and Image Representation, 71, 102812.
14. Katirciođlu, F., & cýngýz, Z. (2020). A novel gray image enhancement using the regional similarity transformation function and dragonfly algorithm. El-Cezeri, 7(3), 1201–1219.
15. Pashaei, E., & Pashaei, E. (2023). A fusion approach based on black hole algorithm and particle swarm optimization for image enhancement. Multimedia Tools and Applications, 82(1), 297–325.
16. Zhang, L., & Zhao, L. (2021). High-quality face image generation using particle swarm optimization-based generative adversarial networks. Future Generation Computer Systems, 122, 98–104.
17. Garg, P., & Kishore, R. R. (2020). Optimized color image watermarking through watermark strength optimization using particle swarm optimization technique. Journal of Information and Optimization Sciences, 41(6), 1499–1512.
18. Bhimavarapu, U., &Battineni, G. (2022). Automatic microaneurysms detection for early diagnosis of diabetic retinopathy using improved discrete particle swarm optimization. Journal of Personalized Medicine, 12(2), 317.
19. Sharma, N., & Batra, U. (2021). An enhanced Huffman-PSO based image optimization algorithm for image steganography. Genetic Programming and Evolvable Machines, 22, 189–205.
20. Mienye, I. D., & Sun, Y. (2021). Improved heart disease prediction using particle swarm optimization based stacked sparse autoencoder. Electronics, 10(19), 2347.
21. Ren, Y., Li, G., Liu, S., & Li, T. H. (2020). Deep spatial transformation for pose-guided person image generation and animation. IEEE Transactions on Image Processing, 29, 8622–8635.
22. Cao, Q., Zhang, W., & Zhu, Y. (2020). Deep learning-based classification of the polar emotions of" moe"-style cartoon pictures. Tsinghua Science and Technology, 26(3), 275–286.
23. Chen, H., Xu, Z., Feng, Q., Fan, Y., & Li, Z. (2020). An L0 regularized cartoon-texture decomposition model for restoring images corrupted by blur and impulse noise. Signal Processing: Image Communication, 82, 115762.
24. Su, H., & Fu, W. (2020). Enhancement method for edge texture details of the filmic and visual three-dimensional animation. Multimedia Tools and Applications, 79(23–24), 16351–16367.
25. Acharya, K., & Ghoshal, D. (2021). Central Moment and Multinomial Based Sub Image Clipped Histogram Equalization for Image Enhancement. Int. J. Image Graph. Signal Process, 1, 1–12.
26. Di, C., Peng, J., Di, Y., & Wu, S. (2021). 3D face modeling algorithm for film and television animation based on lightweight convolutional neural network. Complexity, 2021, 1–10.
27. https://github.com/luxiangju-PersonAI/iCartoonFace