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Feature Enhancement Method for Fuzzy Image Using Mathematical Morphology and Deep Learning

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HIGHLIGHTS

- We propose a fuzzy image feature enhancement method.
- By utilizing separable residual dense blocks to enhance the effectiveness of image understanding.
- The Hessian matrix method can improve the accuracy of image analysis.

Abstract: High-definition images can provide valuable reference for research in fields such as medical image analysis and machine vision. Therefore, image feature enhancement is performed to obtain high-quality images. Conventional methods for image feature enhancement extract features only from a single scale, resulting in low image information entropy. To address this issue, a fuzzy image feature enhancement method using mathematical morphology and deep learning (FIFEMD) is proposed. First, a near-infrared transmission light source is used as the main light source to construct a capture platform, and the grayscale values are normalized and filtered. Second, basic mathematical morphology operations are employed to remove noise points in the original image, and a separable residual dense block is used to extract multi-scale features from the image. Finally, the generated image features are fused and reconstructed using the Hessian matrix method to achieve image feature enhancement. Experimental results demonstrate that the images processed using the FIFEMD method have higher information entropy values, with entropy values above 6.75. The processing time is approximately 2.5 s, indicating high efficiency. Therefore, the FIFEMD method can achieve better image feature enhancement.

Keywords: Fuzzy images; feature enhancement; mathematical morphology; deep learning; information entropy.

INTRODUCTION

The method of fuzzy image feature enhancement can obtain more image information based on the original image data, which is of great assistance in image analysis work. Therefore, image feature enhancement methods are widely applied in the fields of medicine, architecture, and engineering to analyze the information data of existing images [1]. By enhancing the features of the original image, not only can the noise in the original image be filtered out, but also clearer image data can be obtained, effectively reducing the difficulty of image detection work [2-3]. However, in current research, the low degree of feature extraction leads to unsatisfactory results in image feature enhancement. Therefore, a new image feature enhancement method needs to be proposed to optimize the enhancement effect and extract more image information.

In the existing research work, HuH and coauthors [4] took the image of underwater vision SLAM as the research object, and reduces the image edge noise by filtering and dusting the image. At the same time, by counting the pixel distribution in the region of uniform and sufficient illumination, we get the similarity law of environmental features, and solve the underwater illumination model to reduce the image to the state of balanced illumination as a way to enhance the features of the image, and then realize the extraction of more effective feature points. However, the efficiency of this method of image feature enhancement is low. Ren J and Liu C [5] used an adaptive hyper-pixel clustering algorithm to enhance the features in the hyper-pixel region, and uses the enhanced features to train a classifier model to improve the feature expression ability and classification accuracy, thus improving the image quality and classification results. However, the visual enhancement effect of this method is poor. He L and coauthors [6] clustered the high-frequency information and low-frequency information in the image so as to improve the gray level variability of the image, reduce the difficulty of feature extraction, and ultimately achieve the contrast enhancement of the image while keeping the number of gray levels unchanged. However, the brightness of the image of this method is poor. Marcin A and coauthors [7] used partial differential equations to construct an image edge detection algorithm to extract image features in the edge region. The principal direction of each pixel in the image is estimated by calculating the direction field. Then, the image is enhanced according to the direction field using morphological expansion operation, and finally a clear image is obtained. However, the method has poor local contrast. Mondal S and coauthors [8] combined Discrete Cosine Transform (DCT) coefficient mapping and Gray Wolf Optimization (GWO) algorithms to maintain the original image features and to generate contrast enhanced images. The DCT parameters are adjusted to avoid saturation of pixel values, and the GWO uses different parameters to formulate an objective function that maintains the features of the original image. But this method has low image information entropy. All of the above methods can achieve image feature enhancement to a certain extent. However, there is still much room for improvement in image feature enhancement effect, i.e., there is still potential for improvement and optimization in balancing contrast enhancement and detail preservation, handling complex scenes, establishing objective evaluation criteria, and improving real-time processing capability.

Mathematical morphology and deep learning have found wide applications in the field of image processing, including but not limited to image enhancement, feature extraction, noise reduction, and edge detection. Mathematical morphology, as a shape-based image analysis tool, reveals the essential features of image structure by processing the image with structuring elements. This method has shown excellent performance in filtering, edge detection, image thinning, image thickening, and other aspects. Classical algorithms include dilation, erosion, opening, and closing operations, which efficiently achieve feature extraction and improve image quality by interacting with specific structuring elements [9]. Meanwhile, deep learning, especially convolutional neural networks (CNNs), has made revolutionary contributions to image processing. CNNs automatically identify and extract representative features by learning from a large amount of image data, thereby achieving significant results in tasks such as image classification, detection, and enhancement [10]. Recent research has shown that deep learning models, particularly those based on generative adversarial networks (GANs) and attention mechanisms, have demonstrated strong potential in the field of image enhancement [11]. For example, training GANs models to generate high-quality images, combined with the introduction of attention mechanisms, can finely adjust the local regions of the image, further enhancing the effectiveness of image enhancement. Although mathematical morphology and deep learning each have significant applications and achievements in image processing, they are complementary in concept. Mathematical morphology provides a solid theoretical foundation and efficient operational tools, while deep learning introduces adaptive and self-learning capabilities to handle more complex image processing tasks. This paper combines these two fields to achieve more efficient and accurate image processing results. To address the issues present in the aforementioned methods, this paper proposes a fuzzy image feature enhancement method based on mathematical morphology and deep learning (FIFEMD), aiming to effectively and swiftly enhance the features of fuzzy images. Mathematical morphology is a mathematical theory and method used in image processing and analysis. It is based on the concepts of set theory and algebra and extracts structural information from images, improves edge detection, and performs tasks such as noise reduction through morphological operations like dilation, erosion, opening, and closing. Mathematical morphology is effective in handling features related to shape, texture, and structure in images.

Deep learning, a branch of machine learning, mimics the workings of the human brain's neural networks and learns and extracts features from data by constructing multi-layer neural network models. Deep learning typically uses models called deep neural networks, which consist of multiple hidden layers, each containing multiple nodes or neurons. By training these neural networks, deep learning can automatically learn abstract features from input data and utilize them for tasks such as classification, recognition, and regression. In the FIFEMD method can be utilized to improve tasks such as edge detection, noise reduction, and morphological reconstruction in images, while deep learning can be employed to learn and extract higher-level abstract features from images, further enhancing the quality and clarity of fuzzy images. The combination of both approaches can leverage their respective strengths and achieve more effective and accurate image feature enhancement.

The main contributions of this paper are as follows:(1) By employing the basic operations of mathematical morphology to remove noise points in the image, not only does it exhibit effective de-noising results, but it also preserves the details and edge information of the image, improving the image quality and visualization effects. (2) By utilizing separable residual dense blocks to extract multi-scale features from the image, it can effectively utilize multi-level feature information, enhancing the effectiveness of image understanding and processing. Moreover, it possesses advantages such as efficient performance, cross-layer feature fusion, and adaptive feature learning, providing better solutions for image processing and computer vision tasks. (3) The Hessian matrix method can fully utilize multi-scale feature information, improving the accuracy and robustness of image analysis and understanding. Additionally, it preserves local features, provides high-dimensional feature representations, and possesses advantages such as reversibility and stability, offering an effective solution for feature fusion and reconstruction in images. (4) Evaluation metrics indicate that the FIFEMD method demonstrates outstanding performance in the enhancement of fuzzy image features, ensuring both the quality and efficiency of the feature enhancement process.

FIFEMD method

The FIFEMD method for enhancing fuzzy image features involves four steps, as illustrated in Figure1. It can be observed that this paper first conducts image acquisition and preprocessing. Mathematical morphology algorithms are employed to de-noise the acquired images. Then, the de-noised images are fed into a deep learning network. In the deep network learning process, the letter "C" represents a convolutional layer. The input images are first convolved by each convolutional layer, generating a new set of feature maps. These feature maps can be regarded as the feature representations of the original input data at different scales. Second, these feature maps are further processed through activation functions for nonlinear transformations. Finally, by concatenating multiple convolutional layers and other processing layers, the module outputs a set of multi-scale feature representations, where each feature corresponds to information at a different scale. This process allows for the acquisition of multi-scale features of the image, thereby achieving image feature enhancement.

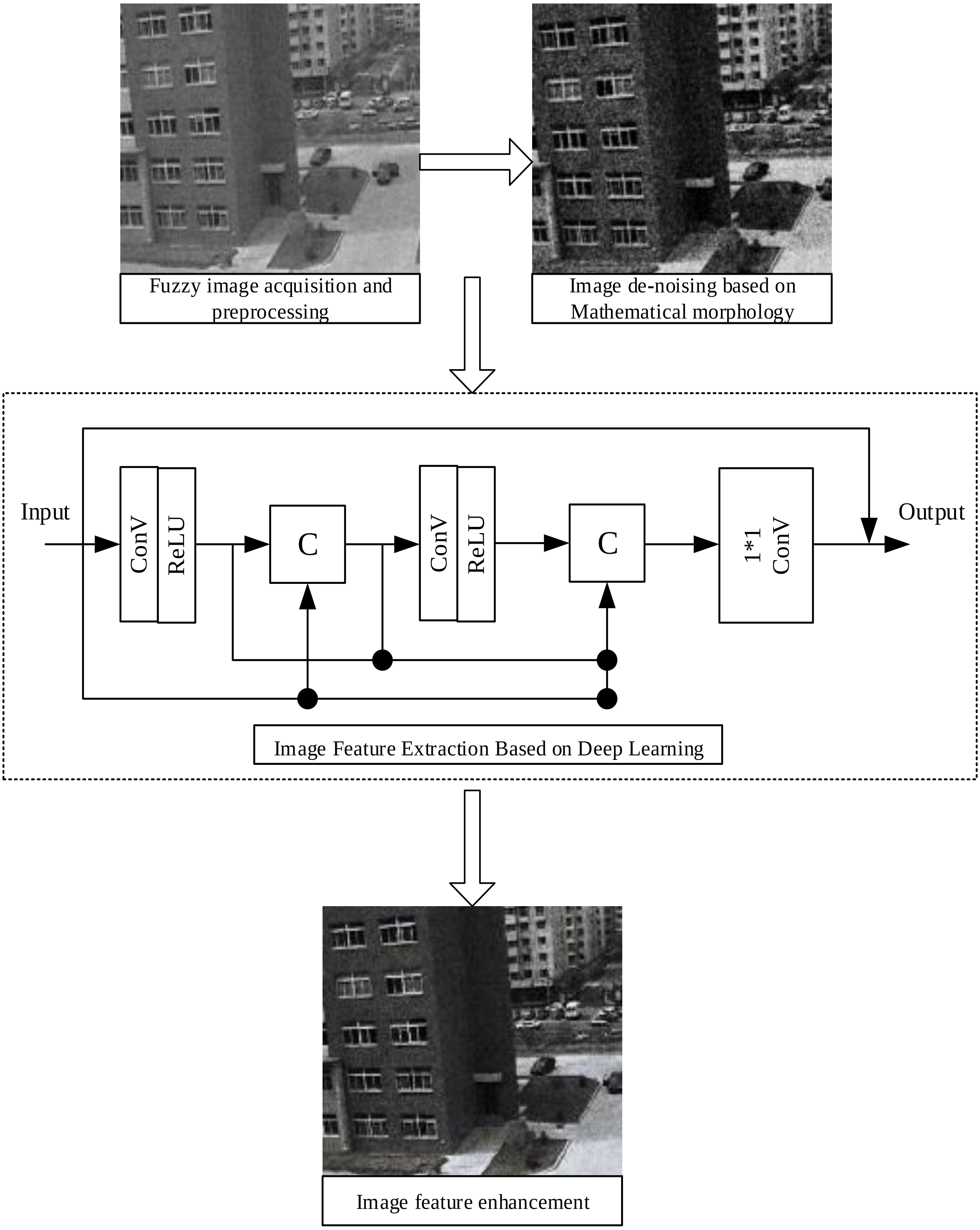

Figure 1. Framework of FIFEMD method

Fuzzy image acquisition and basic processing

To achieve feature enhancement of fuzzy images, this study establishes an image acquisition platform to collect images. The acquired images are then subjected to basic preprocessing, including grayscale normalization and filtering algorithms, to reduce the workload for subsequent image feature enhancement and improve the efficiency of the algorithm [12-13]. To improve the effectiveness of image feature enhancement, the collected images need to possess high recognizability. Therefore, this study utilizes near-infrared transmission light as the primary light source and combines it with reflective light sources for image acquisition. By illuminating the object surface with near-infrared projection light, the image information is highlighted, and the image data is transmitted using a computer [14]. The schematic of the image acquisition platform is shown in Figure 2.

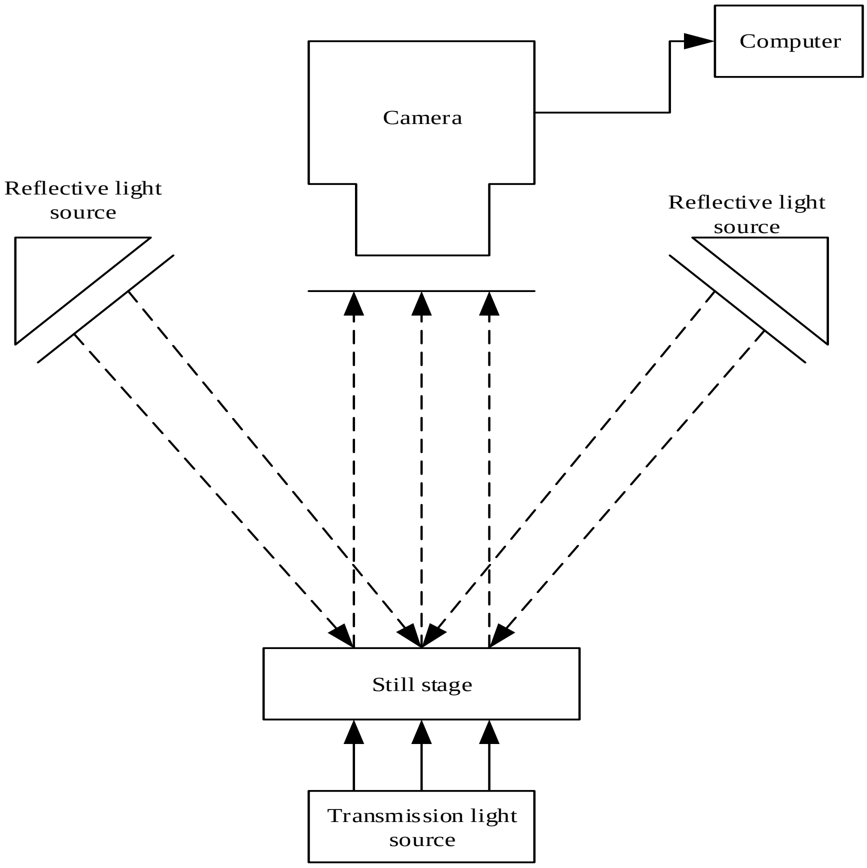

Figure 2. Principle of fuzzy image acquisition platform

Due to the presence of a significant amount of background information and noise in the images captured through the aforementioned capture platform, these uncertain information elements can easily introduce substantial interference to the subsequent image feature enhancement [15]. By analyzing the principles of the aforementioned near-infrared image capture platform, it can be inferred that during the process of capturing fuzzy images, the capture environment, duration, and lighting conditions can lead to noticeable variations in the grayscale levels of the captured images. To mitigate the differences in grayscale levels among the images, it is necessary to normalize the grayscale values. In this study, the mean and variance of the fuzzy images are utilized as normalization factors to achieve a uniform treatment of the images' mean values and variances, thereby enhancing the consistency of the image standards. Assuming that the grayscale values of the original fuzzy images acquired by the aforementioned fuzzy image acquisition platform correspond to $I(x,y)$, the formula for mean and variance processing is as follows [16]:

$$I'(x,y) = M + \sqrt{V\left(\frac{I(x,y)-M}{V}\right)^2} \tag{1}$$

where M and V represent the average and variance sizes corresponding to the grayscale values of the original fuzzy image, respectively. $I'(x,y)$ represents the fuzzy image after normalization processing.

The formula for calculating the average grayscale value of an image is as follows:

$$M = \frac{\max\left(I(x,y)\right) - \min\left(I(x,y)\right)}{N} \tag{2}$$

where $\max\left(I(x,y)\right)$ and $\min\left(I(x,y)\right)$ represent the maximum and minimum grayscale values of the fuzzy image, respectively, N denotes the total number of pixels in the image. Due to the interference from the external acquisition environment during the imaging process, the acquired images often suffer from the defect of edge blurring. Therefore, it is necessary to apply a smoothing filter to the original image [17]. During this process, it is inevitable to lose some high-frequency components, which contain edge information of the image. To effectively address this issue, this study combines the bilateral filtering algorithm to process the original fuzzy image, and the specific processing formula is as follows [18].

$$I_{BF}(x,y)=\frac{\sum_{k,l} I'(x,y)W}{\sum_{k,l} W} \tag{3}$$

where $I_{BF}(x,y)$ represents the grayscale value of the image after filtering processing. k and l represent the neighborhood size of the sampled sample. $I(k,l)$ is the grayscale value of the neighboring image of the sampled sample. W is the grayscale weight coefficient of the image, which can be solved through a similarity factor. The calculation formula is as follows [19]:

$$W=W_d W_r \tag{4}$$

$$W_d=\exp\left(-\frac{(x-k)^2-(y-l)^2}{2\sigma_d}\right) \tag{5}$$

$$W_r=\exp\left(-\frac{\|f(x,y)-f(k,l)\|^2}{2\sigma_r}\right) \tag{6}$$

where W_d represents the spatial similarity factor. W_r is the grayscale similarity factor. σ_d represents the standard deviation of spatial set similarity. σ_r denotes the standard deviation of grayscale similarity. $f(x,y)$ and $f(k,l)$ are the Gaussian function values of the sample image and the neighborhood image, respectively. By above steps, the collection and preprocessing of fuzzy images can be successfully completed, achieving grayscale normalization and filtering to aid in the subsequent image feature enhancement.

Fuzzy Image De-noising Based on Mathematical morphology

After completing the collection and basic processing of fuzzy images, the original fuzzy image data still contains a significant amount of noise. If feature extraction is directly performed on the noisy data, there is a risk of mistakenly extracting noise data as image features, thereby reducing the effectiveness of image feature enhancement. Therefore, this study combines mathematical morphology algorithms to de-noise the fuzzy images. To preserve the edge information and image details of the original image to the maximum extent, the study utilizes dilation and erosion operations on the image, employing basic mathematical morphology operations to remove noise points in the original image and minimize damage to the original image. The implementation process is as follows:

First, the original fuzzy image is subjected to a dilation operation using the opening operation in mathematical morphology to obtain typical marker features in the image. This type of opening operation is also known as the top-hat transform operation, the mathematical expression shown below

$$HAT(f)=f-(f\oplus b) \tag{7}$$

where $HAT(f)$ represents the image after the open operation processing is completed. f is the original fuzzy image. b represents typical structural elements in the original image [20].

Through the aforementioned top-hat transform operation, the peak features in the original image can be extracted. Similarly, to obtain the valley features of the original image, an erosion operation is applied using the closing operation in mathematical morphology, known as the down-hat transform. The mathematical expression for the down-hat transform is shown below

$$HAT(-f)=(f\oplus b)-f \tag{8}$$

where $HAT(-f)$ represents the image after closed operation processing is completed.

Through the aforementioned operations, dark spots smaller than the typical structural size in the original image can be removed, while the opening operation preserves bright spots larger than the original structural size. Therefore, by performing opening and closing operations on the original image, the bright and dark detailed features in the image can be effectively retained. The opening and closing operations mentioned above refer to the dilation and erosion operations. The illustrations of these operations are shown in Figure 3.

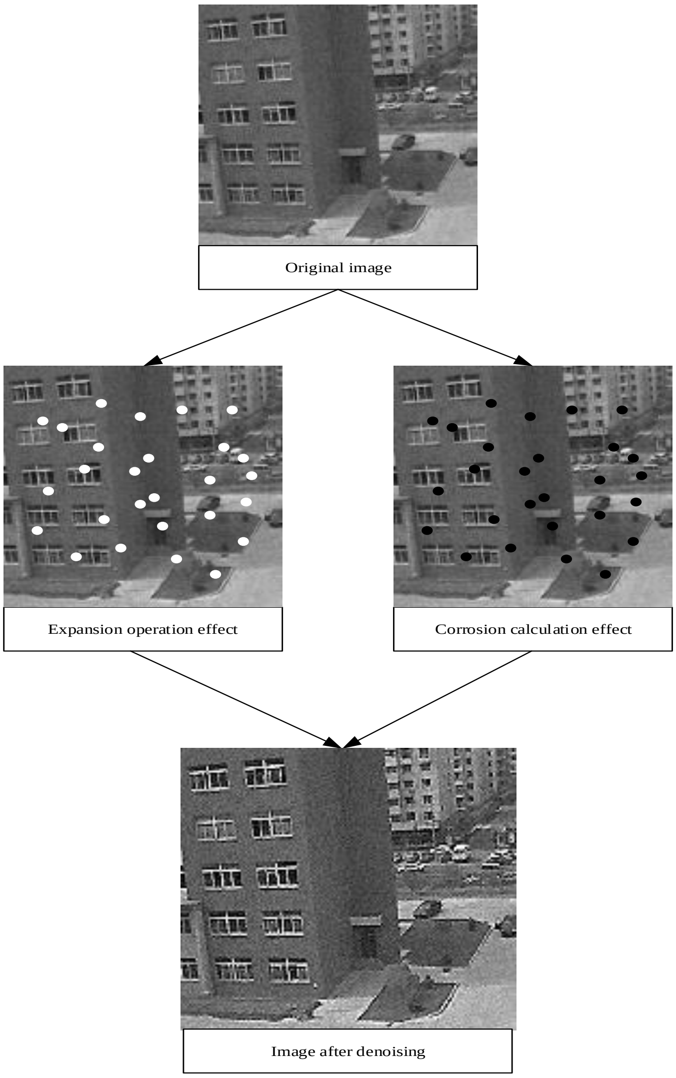

Figure 3. Effect of expansion and corrosion operations

By performing the dilation and erosion operations on the original image as described above, the extraction of brightness and darkness details is achieved. The two resulting images from these operations are then combined and reconstructed to obtain the de-noised image after processing. The reconstruction formula is shown below

$$g = f + 0.5\sum_{i=1}^{n} HAT(f) - 0.5\sum_{i=1}^{n} HAT(-f) \tag{9}$$

where g represents the image after de-noising is completed. n is the number of image structural elements.

Image multi-scale feature extraction based on deep learning algorithm

To ensure that the enhancement process of the image can target its typical features, this study employs a deep learning algorithm [21-22] to construct a multi-scale feature extraction module. This module effectively extracts the typical features of the image and consists primarily of separable residual dense blocks (SRDB). Each SRDB module consists of 3 convolutional layers, with each convolutional layer containing 32 filters of sizes 3x3, 5x5, and 7x7. The activation function applied after each hidden layer is ReLU. The structure of this module is illustrated in Figure 4.

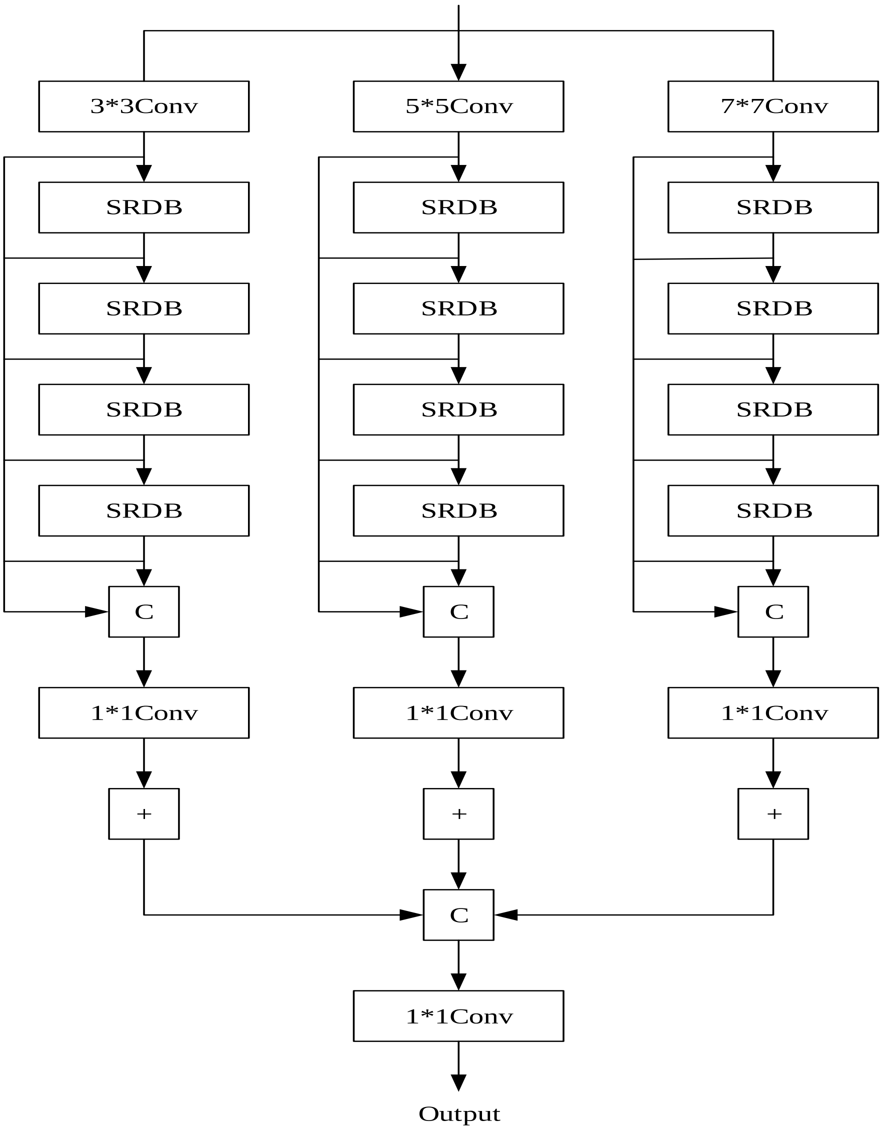

Figure 4. Structure of multi-scale feature extraction module based on deep learning algorithm

In Figure 4, 3*3Conv represents a 3x3 convolutional layer. Convolutional layers extract features from input data through convolutional operations. "3x3" indicates that the size of the convolutional kernel is 3x3. Similarly, 5*5Conv represents a 5x5 convolutional layer, and 7*7Conv is a 7x7 convolutional layer. SRDB represents a special network module that typically consists of multiple densely connected convolutional layers and skip connections. It enhances the representation capability of features. SRDB module can extract higher-level features by stacking multiple convolutional layers (such as 3x3, 5x5, 7x7) while preserving low-level feature information. C denotes a convolutional layer used to extract features from input data. 1*1Conv represents a 1x1 convolutional layer. The 1x1 convolutional kernel is used in convolutional layers for linear combinations and dimensionality reduction between channels. By using 1x1 convolutions, the number of channels in the feature map can be altered, thereby controlling the number of parameters and computational complexity in the network.

First, three convolutional kernels of different sizes are used to extract shallow-level features from the image. Then, four densely connected separable residual dense blocks are employed to extract intermediate and high-level semantic information from the image data, and the extracted results are transmitted as hierarchical features. Finally, a standard convolutional channel is connected to output the feature results. To preserve the sharpness information of the image edges, this study constructs a global similarity loss function to calculate the pixel-level loss of the image. The specific function expression is shown below [23].

$$L_1 = E\left[\left\| Y - G(X) \right\|\right] \tag{10}$$

where $G(X)$ represents the generated image. Y represents the expected domain image. X represents the source domain image. L_1 represents the similarity loss value. At the same time, to sharpen the edges of the original image, it is necessary to calculate the gradient difference loss of the image. The calculation formula is as follows:

$$L_{gd} = E\left[\left\|\lambda_Y - \lambda_{G(X)}\right\|^2\right] \tag{11}$$

where $\lambda_{G(X)}$ represents the gradient value of generated image $G(X)$ at pixel (x,y). λ_Y is the gradient value of the expected domain image Y at pixel (x,y). L_{gd} represents the gradient difference loss value of the image.

To ensure that the extracted image features have a certain amount of typical image information, it is also necessary to calculate the content perception loss value of the image. The calculation formula is as follows:

$$L_{content} = E\left[\left\|\varphi_Y - \varphi_{G(X)}\right\|^2\right] \tag{12}$$

where $\varphi_{G(X)}$ represents the image content perception loss value corresponding to the generated image. φ_Y denotes the content perception loss value of the expected domain image after training, $L_{content}$ represents the total amount of content perception loss value.

To obtain the final loss function, the three types of losses are combined with weighted sums. The choice of weights depends on specific application requirements and the importance assigned to each loss term. Therefore, the final loss function is

$$L = \gamma_1 L_1 + \gamma_2 L_{gd} + \gamma_3 L_{content} \tag{13}$$

where $\gamma_1, \gamma_2, \gamma_3$ is adjusting the weight parameters of each loss item.

By following the above steps, multi-scale feature extraction of fuzzy images can be completed, and loss values can be controlled based on the extracted features to ensure that the extracted features have high sharpening details and features.

Image feature enhancement

To address the extracted multi-scale features, this study integrates the above process by constructing an image feature enhancement algorithm to achieve image feature enhancement. The algorithm involves normalizing the grayscale values of the fuzzy image, applying bilateral filtering for de-noising, and calculating derivatives of the image based on different scale factors. The feature values are then obtained by computing the eigenvalues using the Hessian matrix for multi-scale feature fusion and output. In this regard, the study employs histogram-based enhancement techniques to process the extracted feature data. The processing formula is shown below.

$$I_i = t \times cf(I_i) \times \mu \times p \tag{14}$$

where μ represents the gradient adjustment coefficient. $cf(I_i)$ is the gradient value after interval equalization. p represents the probability density value. t represents the histogram enhancement threshold. I_i is the grayscale value of the image after enhancement processing. In which, the gradient value of interval equalization can be calculated through the gray distribution probability, and the calculation formula is as follows:

$$cf(I_i) = \frac{\sum d(k)}{t} \tag{15}$$

where $d(k)$ represents the probability of image gray distribution. The generated image features are fused and reconstructed using the Hessian matrix method. The Hessian matrix is a second-order derivative matrix that describes the local curvature of a multivariable function. For image processing tasks, the Hessian matrix can be used to evaluate the degree of change in features points, edges, textures, and other information in an image. In image feature enhancement algorithms, through the computation of the Hessian matrix, multi-scale analysis and fusion of image features can be achieved. Specifically, during the image processing

process, by taking derivatives of the image with respect to different scale factors, a set of gradient values can be obtained. Utilizing these gradient values to calculate the Hessian matrix, and then computing the eigenvalues and eigenvectors of the Hessian matrix, crucial information about image features such as corners and edges can be obtained. The reconstructed image expression obtained from this process is as follows.
and the matrix expression is as follows:

$$X_i = \frac{\mathbf{H} \cdot div}{cf(I_i)} \tag{16}$$

where X_i represents the fuzzy image after reconstruction. div represents the divergence operator. $\mathbf{H}$ represents the Hessian matrix. After the above steps, the reconstruction of fuzzy images can be completed, and the extracted main features can be fused to complete image feature enhancement.

By following the aforementioned steps, the fusion processing of image features is completed, thereby achieving image feature enhancement. Combining this section with the aforementioned topics such as image acquisition and pre-processing, image de-noising, and multi-scale feature extraction, the design of the FIFEMD method is concluded.

EXPERIMENTAL ANALYSIS AND RESULTS

Experimental data set

To validate the effectiveness of the FIFEMD method, five conventional fuzzy image feature enhancement methods were selected as comparative objects for the experiment, namely the methods in IDFEA[4], ASPFE[5], NLIEM[6], BHIE[7], and DCTCW[8]. Specifically, the methods in IDFEA[4] and ASPFE[5] were used as control conditions for ablation experiments. By constructing an experimental platform, six image feature enhancement methods were used to enhance the same set of test image data, and the enhancement performance of different algorithms was compared.

The selected datasets for this experiment are the Kodak dataset and the DIV2K dataset. The Kodak dataset is commonly used to evaluate the performance of image super-resolution algorithms. The images in this dataset are corrupted by blur and compression. The images in the dataset come from different scenes such as cities, seascapes, and portraits. The DIV2K dataset is a high-resolution image dataset that contains 2,000 high-resolution images from various scenes including cities, natural landscapes, and animals. These images have a resolution of 1080p (1920x1080) or higher, and each image has a corresponding low-resolution version. Randomly selected fuzzy image data were used as the test dataset and training dataset for this experiment, and the specific dataset settings are shown in Table 1.

Table 1. Experimental Dataset Parameter Settings

Data sets	Kodak	DIV2K
Total Data	1500	2000
Test set	300	400
Training set	1200	1600

In this experiment, the initial learning rate of the FIFEMD method was set to 0.002, and the original image size was 360×360×25. During actual testing, the two datasets were mixed to create a combined dataset, from which the mixed test dataset was used for evaluation. A total of 3500 images were used, with 700 images as the test set and 2800 images as the training set. The learning rate momentum was set to 0.9, weight decay coefficient was set to 0.0001, and the Epoch was set to 140. Some sample images from the dataset are shown in Figure 5.

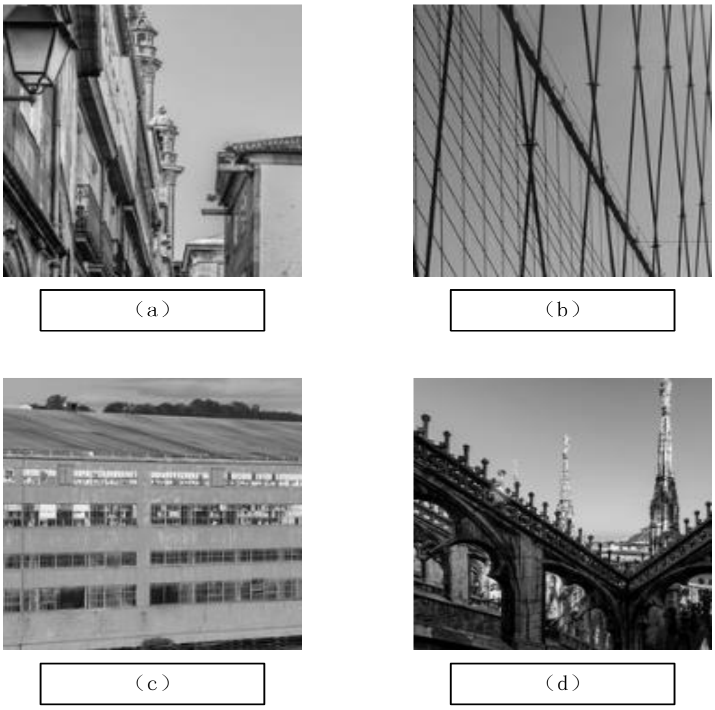

Figure 5. Original images of partial dataset

Evaluation metrics

To improve the reliability of the experimental results, five metrics were selected in this study to compare the practical performance of different image feature enhancement methods. These metrics include visual enhancement effect, processing time, standard deviation, information entropy, and image mean. Among them, processing time, standard deviation, information entropy, and image mean were used for comparative experiments. These four metrics can demonstrate the enhancement effects of image feature enhancement methods from the perspectives of algorithm execution efficiency, local contrast, image information richness, and image brightness. In addition, this study conducted ablation experiments to compare the feature enhancement effects of different methods. The experimental comparative algorithms in this study include the methods in IDFEA[4], ASPFE[5], NLIEM[6], BHIE[7], and DCTCW[8], and the FIFEMD method. The practical application effects of different methods were evaluated by comparing the visual enhancement effects of fuzzy images, image feature enhancement efficiency, image mean, image standard deviation, and image information entropy.

To further analyze the performance of the FIFEMD method in enhancing features of fuzzy images, an ablation experiment was conducted. The experiment involved using the method in IDFEA[4] and the method in ASPFE[5] for the ablation analysis. The visual enhancement effect was taken as the experimental metric to evaluate the performance of the models.

The processing time of image feature enhancement is an important metric for evaluating processing efficiency. A shorter processing time indicates higher efficiency, which means that the method can complete image feature enhancement more quickly and obtain higher-quality images. The formula for processing time is as follows:

$$T = T_s - T_0 \tag{17}$$

where T_s represents the processing end time. T_0 is the initial processing time.

The image mean is selected as an evaluation criterion. This metric can be used to characterize the brightness variations in an image. By calculating the mean value of an image, the brightness information of the image can be obtained. A higher mean value indicates a brighter overall image, while a lower mean value indicates a darker overall image. The formula for calculating the image mean is as follows:

$$Z = \frac{I_i}{N} \tag{18}$$

The selection of image standard deviation can represent the local contrast of an image. A smaller standard deviation indicates higher local contrast, resulting in better enhancement effects. The formula for standard deviation is as follows:

$$\sigma = \sqrt{\left[\frac{\sum(\chi - Z)}{N}\right]} \tag{19}$$

where σ represents the standard deviation. $\sum$ stands for Summation. χ represents the grayscale value of each pixel.

Image information entropy is selected as an evaluation metric. This metric can be used to measure the richness of information contained in an image. A larger information entropy value indicates a higher amount of information in the image. The formula for image information entropy is as follows:

$$\varpi = -\sum\left(d(k) * \log_2 d(k)\right) \tag{20}$$

To further validate the feature enhancement effect of the FIFEMD method on blurred images, peak signal-to-noise ratio (PSNR) is selected as the evaluation metric for measuring the enhancement effect of blurred image features, with the expression as follows:

$$P = 10\log\left(\frac{255 \times M \times N}{2\|x - y\|^2}\right) \tag{21}$$

where $M \times N$ represents the number of pixels in the blurred image, x and y represent the images before and after blurred image enhancement, respectively.

Results and discussion

In this experiment, six image feature enhancement methods were applied to enhance the image data in the test set. The following are partial comparison images showcasing the enhancement effects obtained.

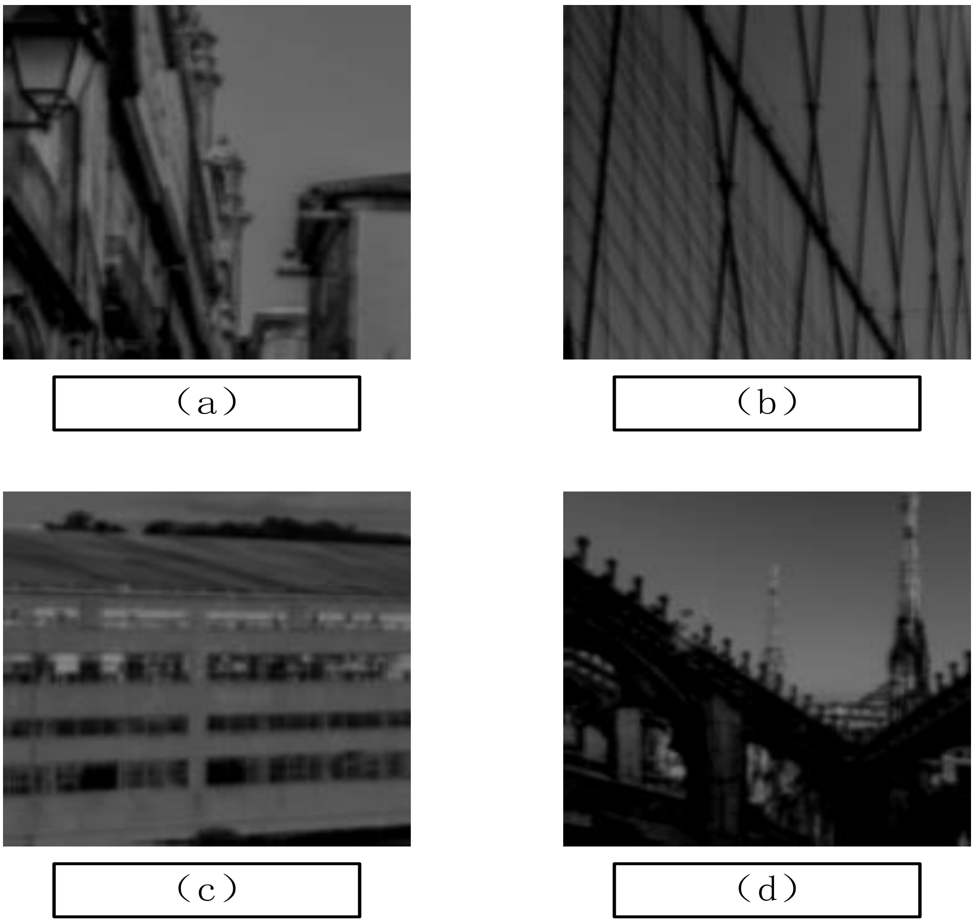

Figure 6. Visual Enhancement Effect of IDFEA [4] Method

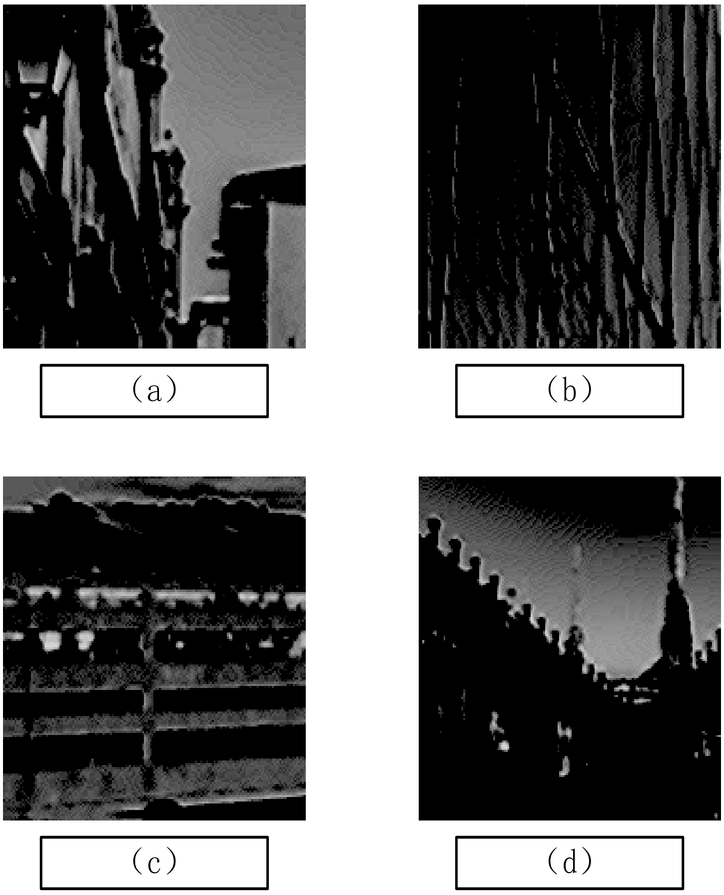

Figure 7. Visual Enhancement Effect of ASPFE[5] Method

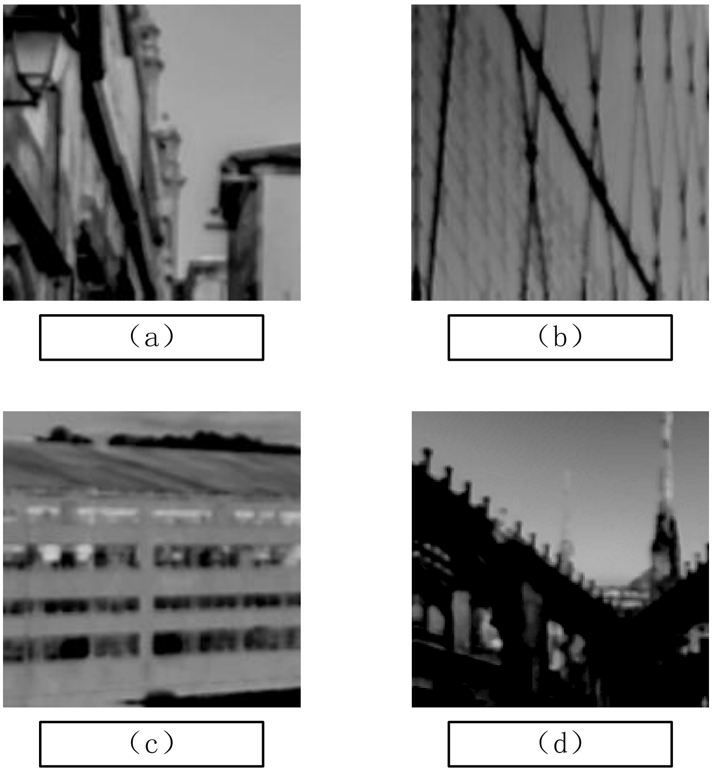

Figure 8. Visual Enhancement Effect of NLIEM [6] Method

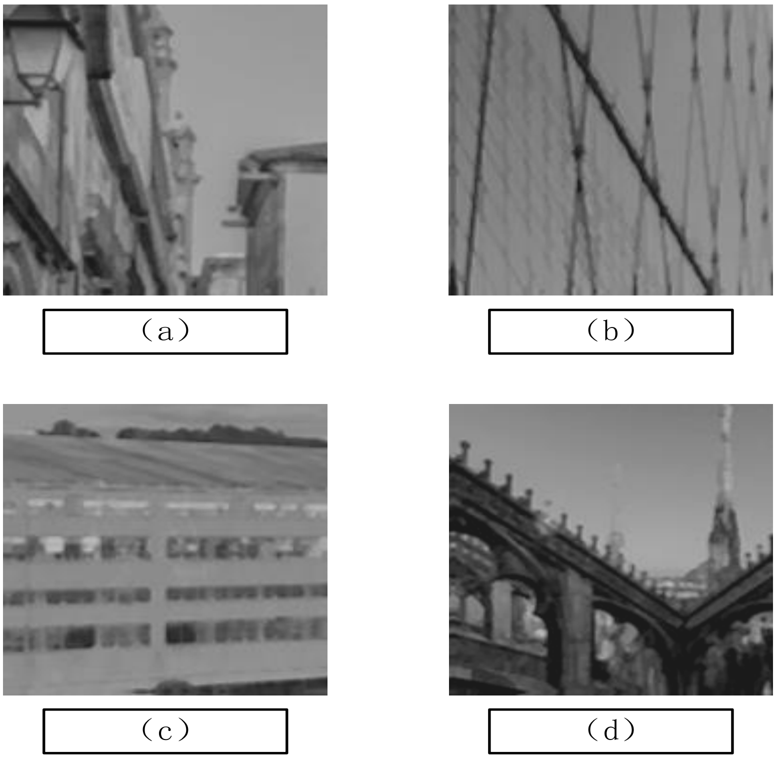

Figure 9. Visual Enhancement Effect of BHIE [7] Method

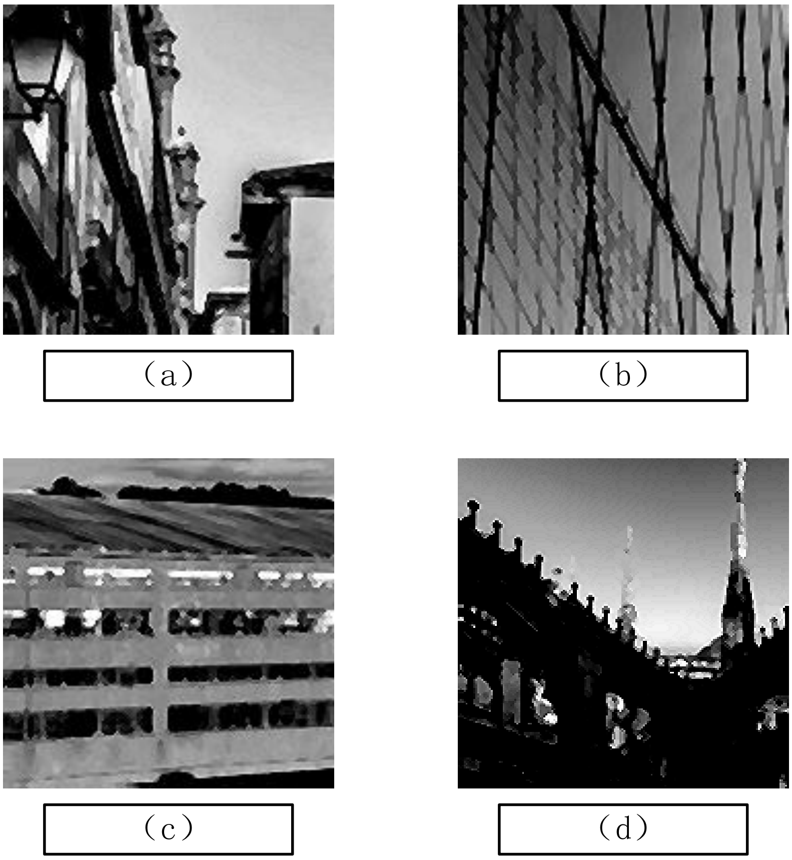

Figure 10. Visual Enhancement Effect of DCTCW [8] Method

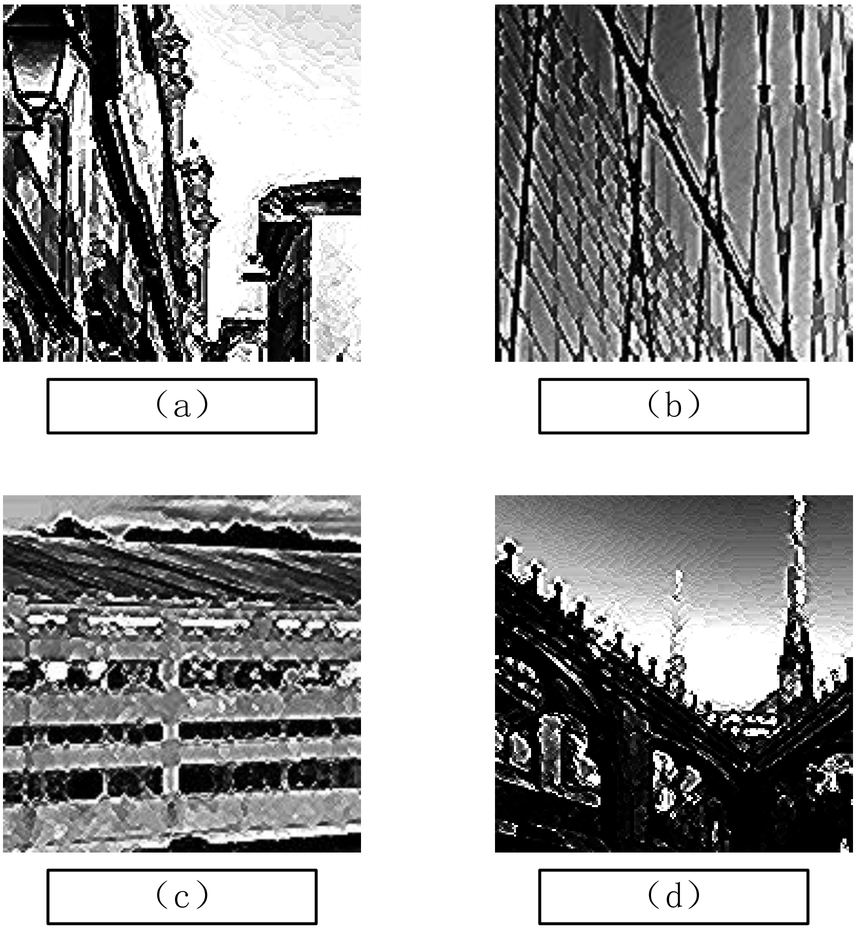

Figure 11. Visual enhancement effect of the FIFEMD method

The visual enhancement results of the ablation experiments in Figures 6 to 11 show the following: Images processed by the method in IDFEA[4] exhibit darker colors and lower clarity, possibly due to the filtering and denoising process being unable to effectively differentiate between real signals and noise, resulting in loss of image details; Images processed by the method in ASPFE[5] have darker colors compared to IDFEA[4], with only rough outlines visible, as this method neglects some important feature information during the enhancement process, impacting the final image quality and classification results; Images processed by the method in NLIEM[6] have blurrier contours, likely because the clustering process fails to effectively distinguish between information of different frequencies, resulting in a less pronounced feature enhancement effect; Images processed by the method in BHIE[7] have lighter colors due to the edge detection algorithm based on partial differential equations being sensitive to noise, leading to instances of false positives and false negatives; Images processed by the method in DCTCW[8] show a poor enhancement effect on image details, possibly because the adjustment of DCT parameters does not adequately consider the specific properties of the image, resulting in inaccurate contrast adjustments. In contrast, images processed by the FIFEMD method exhibit good clarity and sharp detail regions, attributed to the morphological operations in FIFEMD method that help eliminate noise points and isolated points in the image, preserving the structural information and enhancing the image quality and contrast. This indicates that compared to other traditional methods, the FIFEMD method holds a significant advantage in overall visual effects such as image grayscale and clarity, resulting in superior visual enhancement effects.

In this experiment, the processing time of image feature enhancement was used as the evaluation indicator, and to compare the efficiency of image feature enhancement. It aimed to investigate the changes in the processing efficiency of the algorithms for the same set of images under the same iteration count. The specific experimental results are shown in Figure 12.

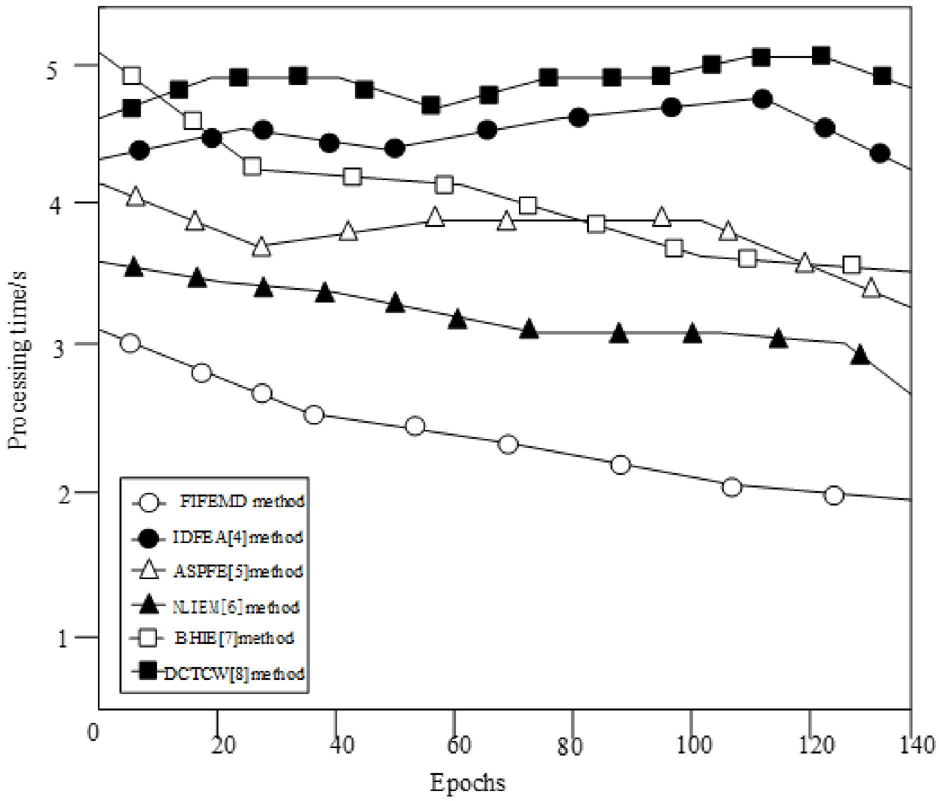

Figure 12. Comparison Results of Enhancement Efficiency of Different Enhancement Methods

The experimental results in Figure 12 indicate that different methods require varying processing times when enhancing different images. Through numerical comparisons, it can be observed that the FIFEMD method has an average processing time of around 2.5s, the method in IDFEA[4] has an average processing time of around 4.5s, the method in ASPFE[5] has an average processing time of around 3.8s, the method in NLIEM[6] has an average processing time of around 3.3s, the method in BHIE[7]has an average processing time of around 4s, and the method in DCTCW[8] has an average processing time of around 4.8s. This confirms that the image feature enhancement efficiency of the FIFEMD method is superior to conventional image feature enhancement methods.

The mean value of an image can be used to characterize the brightness variations of the image. Experimental results obtained by statistical analysis of image mean values are presented in Table 2. The unit for image mean values is pixels.

Table 2. Comparison Results of Image Mean Values

Epochs	IDFEA[4] method	ASPFE[5] method	NLIEM[6] method	BHIE[7] method	DCTCW[8] method	FIFEMD method
20	116	114	109	92	99	128
40	101	108	95	107	93	126
60	108	109	110	114	110	128
80	115	102	115	98	113	126
100	118	116	116	112	112	121
120	119	118	117	115	114	122
140	121	120	119	118	117	124

The results from Table 2 indicate that the image mean values of the images processed using the FIFEMD method are all above 120 pixels. In comparison, The image mean values processed by the method in IDFEA[4] ranges from 101 to 121 pixels, the image mean values processed by the method in ASPFE[5] ranges from 102 to 120 pixels, the image mean values processed by the method in NLIEM[6] ranges from 95 to 119 pixels, the image mean values processed by the method in BHIE[7] ranges from 92 to 118 pixels, and the image mean values processed by the method in DCTCW[8] ranges from 99 to 117 pixels. The image mean values achieved by the FIFEMD method exceed those obtained by the other five methods, demonstrating that the images processed by the FIFEMD method possess higher brightness and exhibit superior image processing results.

The image standard deviation can characterize the local contrast of an image. A smaller standard deviation indicates higher local contrast, leading to better enhancement effects. The experimental results are shown in Figure 13.

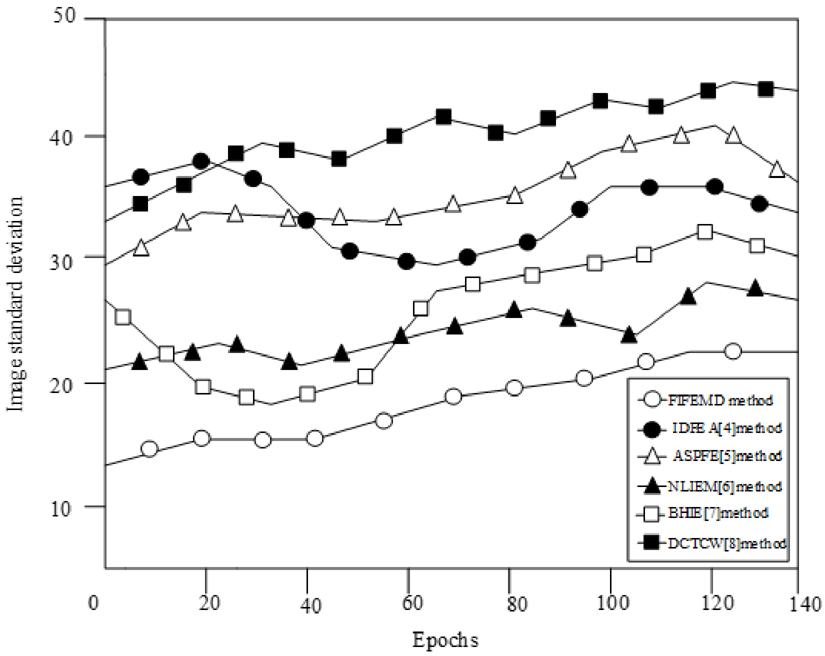

Figure13. Comparison Results of Image Standard Deviation

According to results in Figure 13 reveal that the image data processed using the FIFEMD method in this study exhibit a mean standard deviation value below 20. In comparison, the mean standard deviation values of images processed by the methods in IDFEA[4] is around 38, ASPFE[5] is around 37, NLIEM[6] is around 23, BHIE[7]is around 25, and DCTCW[8] is around 40, respectively. These findings indicate that the FIFEMD method is able to enhance the local contrast of images, resulting in superior image feature enhancement effects.

The image information entropy can be used to quantify the level of information richness in an image, where a higher entropy value indicates a greater amount of information contained in the image. The specific experimental results are presented in Table3. The unit for information entropy is J·K-1.

Table 3. Comparison Results of Image Information Entropy

Epochs	IDFEA[4] method	ASPFE[5] method	NLIEM[6] method	BHIE[7] method	DCTCW[8] method	FIFEMD method
20	5.25	4.32	5.03	5.32	5.38	5.41
40	4.28	4.25	4.56	4.08	4.13	4.66
60	5.78	4.28	5.64	5.15	5.48	5.86
80	4.30	4.28	4.15	4.18	4.20	4.82
100	6.74	7.08	7.06	6.75	6.84	7.09
120	6.75	7.09	7.07	7.04	6.92	7.16
140	7.02	7.20	7.13	7.08	7.02	7.29

The experimental results in Table 3 demonstrate that the mean information entropy of the images processed using the FIFEMD method in this study is 6.04. In comparison, the mean information entropy values of images processed by the methods in IDFEA[4] are 5.73, ASPFE[5] are 5,50, NLIEM[6]are 5.80, BHIE[7]are 5.65, and DCTCW[8]are 5.71, respectively. The mean information entropy values of the five conventional methods are below 6.0. These findings provide evidence that the FIFEMD method effectively preserves information in the images.

PSNR is a metric used to measure the quality of an image; a higher value indicates less difference between the processed image and the original image, indicating better quality. The results are shown in Figure 14.

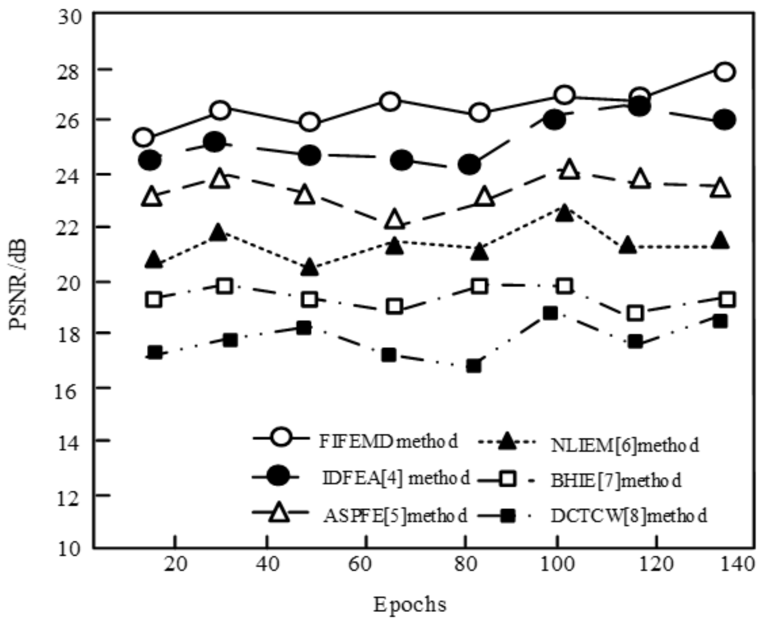

Figure 14. Comparison results of PSNR

According to Figure 14, the PSNR of the processed images using the FIFEMD method reaches a maximum value of 28 dB. In comparison, the maximum PSNR values achieved by the methods in IDFEA[4], ASPFE[5], NLIEM[6], BHIE[7], and DCTCW[8] are 27 dB, 24 dB, 23 dB, 20 dB, and 19 dB, respectively. The PSNR of FIFEMD method is consistently higher than other methods, indicating superior image enhancement effects and minimal differences between the processed and original images.

In summary, based on the visual enhancement effect, enhancement time, image mean values, image standard deviation, image information entropy, and PSNR as six indicators of image enhancement, the FIFEMD method outperforms five conventional methods in terms of enhancement performance. It can improve image brightness and contrast in a shorter time, while retaining more image information, demonstrating superior image feature enhancement performance.

CONCLUSIONS

To address the limitations of traditional methods in enhancing features of fuzzy images, this study proposes a FIFEMD method. First, a near-infrared transmission light source is used as the main light source to construct a capture platform, and the grayscale values are normalized and filtered. Then, basic mathematical morphology operations are employed to remove noise points from the original image, and a separable residual dense block is used for multi-scale feature extraction. Lastly, the generated image features are fused and reconstructed using the Hessian matrix method to achieve image feature enhancement. Experimental results demonstrate that the images processed using this method exhibit better visual enhancement effects. The mean processing time is around 2.5s, indicating high efficiency. The image mean values are all above 120 pixels, indicating higher brightness. The mean standard deviation is within 20, enhancing the local contrast of the image. The image formation entropy is above 6.75, effectively preserving information in the image. Therefore, this method has certain application value. However, there are still limitations and shortcomings in this study. For example, it relies on training data: deep learning methods typically require a large amount of annotated data to establish accurate models. Insufficient or inaccurate annotation data may affect the performance and generalization ability of the model. There are complex factors in images such as background, noise, or color. Effectively enhancing image features under these complex conditions remains a challenging problem. In future works, it is important to establish larger and more diverse image datasets with accurate annotations to improve the performance and generalization ability of deep learning models. Furthermore, exploring the integration of multiple modalities of information into feature enhancement processing, such as color and texture information, will improve the processing effects for complex images and enable the proposal of more detailed feature enhancement methods.

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