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Design of Hybrid Filter for Denoising Images Using Fuzzy Network and Edge Detecting

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Abstract

In this paper, a novel method of hybrid filter for denoising digital images corrupted by mixed noise has been presented. The proposed design of hybrid filter utilizes the concept of neuro fuzzy network and spatial domain filtering. This method incorporates improved adaptive wiener filter and adaptive median filter to reduce white Gaussian noise and impulse noise respectively. Selection of filters depends upon the performance of the impulse noise detection process. The edge detector is capable of extracting edges from filtered images which has been blurred due to different filtering actions. Optimization of neuro fuzzy network training with its internal parameters is collectively accomplished with different natural and synthetic images. Data accomplished from the edge detector, noise filter with the corrupted image together form the training data set. The most distinctive feature of the proposed operator over most other operators is that it offers excellent line, edge, detail, and texture preservation performance while, at the same time, effectively removing noise from the input image.

Keywords: Image restoration, neuro fuzzy spatial filter, Hybrid filter, noise reduction

1. Introduction

Any image acquired by a device is susceptible of being degraded by the environment of acquisition and transmission. The restoration of images tries to minimize the effects of these degradations by means of a filter. Therefore, a fundamental problem in the image processing is the improvement of their quality through the reduction of the noise that they can contain being often known as "cleaning of images". A great variety of techniques dedicated to carry out this task exist. Each of them depends on the types of the noise in images. During image acquisition, the photoelectric sensor induces the White Gaussian noise due to the thermal motion of the electron. Many filters can be used to remove this type of noise; the most famous one is Wiener filter. On the other hand, with the unstable transferring of network some image data may be lost and impulse noise is combined into the image. To remove the impulse noise, many filters are designed; a simple and effective one is Median filter. Gaussian and Impulse noise together named as mixed noise. Neither Wiener filter nor Median filter alone can efficiently reduce this mixed noise. This in turn insists the need for the investigation of new filters.

In recent years many researchers are interested in this area and study the performance of the noise removing filters for image transmissions. Several filters have been studied and implemented for noise reduction. Median operation is combined into sigma filter to enhance the polluted image by L.Alparone et al [1]. An enhanced version of Lee's sigma filter is derived for filtering of images affected by multiplicative noise with speckle statistics. A new edge-preserving filter which is called the mean and median hybrid (MMH) filter is developed to achieve all kinds of noise removal, as well as edge preservation [2]. Hybrid filter that consists of a nonlinear filter and a fuzzy weighted linear filter is derived to reduce the mixed noise. They adopted the first part uses the statistics techniques are used to remove the large magnitude impulsive noise then the second part uses a weighted average linear filter to remove additive Gaussian noise and small ripple impulsive noise [3]. Three variants are combined in trimmed mean filter by fuzzy set to get better noise smoothing result [4]. J.H.Wang et al proposed histogram method is used as the input of fuzzy filter to remove the heavy tailed noise [5].

Chio and Krishnapuram [6] developed one new approach to image enhancement based on fuzzy logic technique. Here, three filters have been introduced for removing impulse noise, smoothing out non-impulse noise and enhancing edges. Histograms of homogenous image regions are used to characterize and classify the corrupting noise [7]. The histogram information of the input image is used to determine the parameters of the membership functions of an adaptive fuzzy filter. The filter is then used for the restoration of noisy images.

The novel hybrid filter combines the advantages of the improved adaptive wiener filter and bilinear interpolation filter for reducing both the white Gaussian noise and impulse noise [8]. Stefan Schulte et al [9] proposed a new filter called *fuzzy impulse noise detection and reduction method* (FIDRM). A new class of nonlinear filters called *vector median-rational hybrid filters* (VMRHF) for multispectral image processing is devised by Lazhar Khriji and Monecef Gabbouj [10]. This filter is a vector rational operation over three sub filters, these filters combine the behavior of rational functions and vector median filters.

A novel switching median filter incorporating with an impulse noise detection method called the boundary discriminative noise detection (BDND) is developed for effectively denoising extremely corrupted images [11]. To determine whether the current pixel is corrupted, the BDND algorithm first classifies the pixels of a localized window, centering on the current pixel, into three groups namely lower intensity impulse noise, uncorrupted pixels, and higher intensity impulse noise. A new operator for restoring digital images corrupted by impulse noise is presented. This operator is a filter obtained by combining a median filter, an edge detector, and a neuro-fuzzy network. The internal parameters of the neuro-fuzzy network are adaptively optimized by training [12].

A majority of above-mentioned filtering methods more or less has the drawback of removing thin lines, distorting edges and blurring fine details in the image during noise removal process. In the last few years, there has been a growing interest in the applications of soft computing techniques, such as neural networks and fuzzy systems, to the problems in digital image processing [4], [9], and [12].

The proposed operator is a hybrid filter constructed by appropriately combining the noise filter, and edge detector with neuro fuzzy network. The rest of the paper is organized as follows. Section 2 explains the structure of the hybrid filter and its building blocks and the implementation of the current work to the test images are discussed. Results of the experiments conducted to evaluate the performance of the suggested algorithm and comparative discussion of these results are projected with tables in Section3.

2. Hybrid Filter

Hybrid filter is obtained by appropriately combining a noise filter, an edge detector with neuro fuzzy network. Fig.1 shows the structure of the proposed hybrid filter. The neuro fuzzy network utilizes the information from the noise filter, as well as from the edge detector as the current input, and the uncorrupted image as the reference output to compute the error function of the system, which is equal to the restored value of the noiseless input pixel.

Figure 1: Proposed structure of the hybrid filter

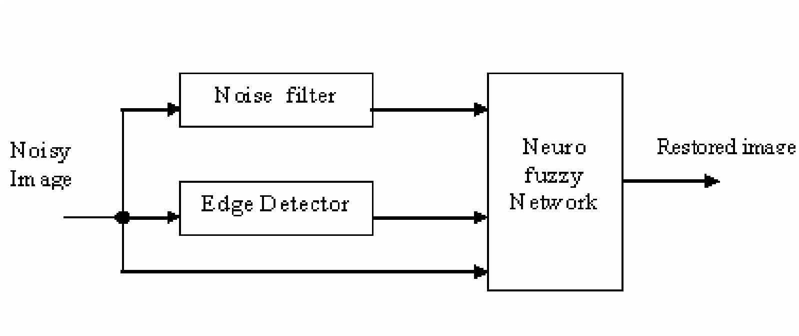
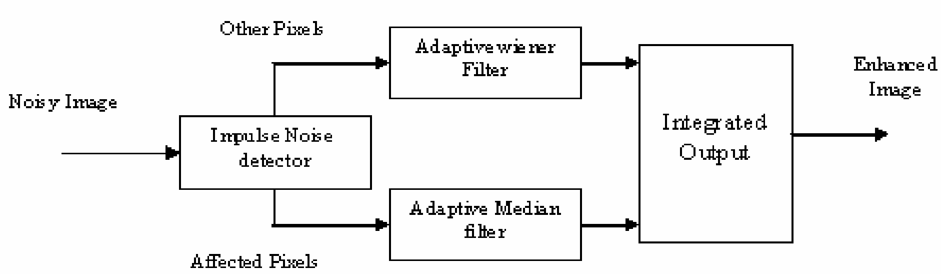


Figure 2: Block diagram of the noise filter



Noise filter is composed of four modules: Impulse noise detector, adaptive wiener filter, adaptive median filter and integrated output. Fig 2.shows the structures of the noise filter. Impulse noise detector divides the set of pixels into two point sub-sets: impulse noise contaminated points and "clean" points. Adaptive wiener filter or adaptive median filter is selected to remove the respective Gaussian noise and impulse noise.

Image contaminated by mixed noise can be modeled by

$$g(x,y) = f(x,y) + n_G(x,y) + n_I(x,y) \tag{1}$$

where $f(x,y)$ and $g(x,y)$ are the gray value of original image and polluted image located at the pixel (x,y), $n_G(x,y)$ and $n_I(x,y)$ are the Gaussian and Impulse noise positioned at the pixel (x,y) respectively.

2.1. Impulse Noise Detector

Impulse noise is a special type of noise, which can have many different causes. Thus, in the case of satellite or TV images it can be caused through atmospheric disturbances. In other applications it can be caused by strong electromagnetic fields, transmission errors, noisy sensors or communication channels. etc., Impulse noise is characterized by short, abrupt alterations of the colors values in the image. The concerned points are changed through overlay of a coincidence value so that they differ significantly from their local neighborhoods and disturb the natural colors run. Thereby the subsequent image processing, analysis and evaluation can be affected. To detect these contaminated points, following rules are devised.

Rule 1: Intensity Feature

A threshold t_1 is introduced to detect the impulse noise contaminated points. The point whose intensity is lower than t_1 or higher than the Max-t_1 would be most likely the noisy point. All these points form a set NP_I.

$$NP_I = set\{(x,y) \mid g(x,y) \le t_1 \, or \, g(x,y) \ge Max - t_1\} \tag{2}$$

Rule 2: Local Feature

According to the continuity of the common images, if the local feature is smooth enough, the current pixel is less likely to be polluted by impulse noise. Suppose $g(x, y)$ is the current pixel intensity and $g(i, j)$ is the pixel intensity of one 8-neighboring pixel of the current pixel. The following noise set $\boldsymbol{NP_L}$ will be formed:

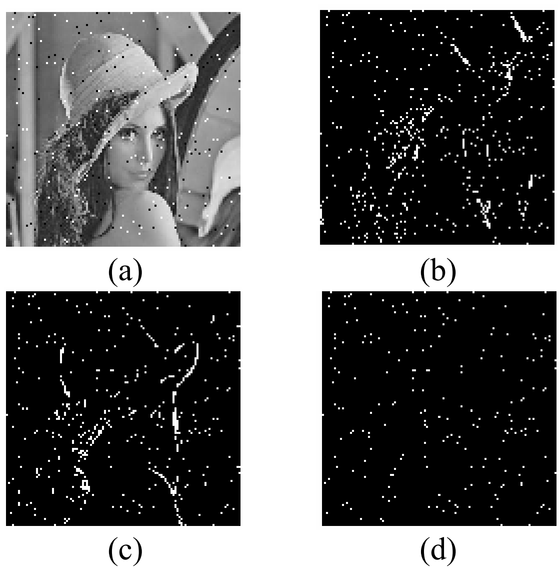
$$NP_L = set\left\{(x,y) \middle| \frac{count(|g(i,j)-g(x,y)| \geq t_2)}{8} \geq t_3\right\} \tag{3}$$

where *count* (condition) indicates the point number that satisfies the condition. Here two thresholds t_2 and t_3 are the intensity differences limit and the proportion limit (in percentage), respectively. Combining the above two rules, the point set for impulse noise set is:

$$NP = NP_I \cap NP_L \tag{4}$$

After the detection of the impulse noise set the complete image is divided into two sets: contaminated pixel set and “clean” pixel set and they have been used for the following process steps. Table 1 shows the result of detection, using “Lena” image, when threshold t_1, t_2 and t_3 are set to 0.15, 0.3 and 0.8.

Figure 3: **(a)** Noisy Lena image **(b)** Noise pixels detected by rule1 **(c)** Noise pixels detected by rule2 **(d)** Common noise pixels found by both rules.



(a) (b) (c) (d)

Table 1: Noise point detection

Noise Value	**10%**	**20%**	**30%**	**40%**
Polluted	26214	52428	78643	104857
NP_I	31556	57354	82891	108451
NP_L	35333	121231	202957	232060
NP	24679	48853	74088	102446

In table1, the first row is the impulse noise value of experimental image. The second row shows the contaminated point number in the polluted image. The third row shows the point number detected by rule1.The fourth row shows the point number detected by rule2. The fifth row shows the common point that is detected in both rules.

2.2. Improved Adaptive Wiener Filter

Images can be corrupted with different kinds of noises. The observed image is a nonlinear combination of the true image signal and noise. The noise could be described by the combination of many different distributions depending on the source of corruption. In image processing, the common source of noise can be described using Gaussian and/or impulsive noise distributions.

To remove Gaussian noise Wiener filter is prescribed. The Wiener filter is the Mean Square Error (MSE)-optimal stationary linear filter for images degraded by additive noise and blurring. Calculation of the Wiener filter requires the assumption that the signal and noise processes are second-order stationary (in the random process sense).Here power spectrum can be deemed as a constant. Then Wiener filter $H(\omega_1,\omega_2)$ is given by

$$H(\omega_1,\omega_2)=\frac{P_f(\omega_1,\omega_2)}{P_f(\omega_1,\omega_2)+P_v(\omega_1,\omega_2)}=\frac{\sigma^2{}_f}{\sigma^2{}_f+\sigma^2{}_v} \tag{5}$$

Where $\sigma^2 f$ is the local variance of the original image and $\sigma^2{}_v$ is the variance of Gaussian noise, respectively. From [7] $h(x,y)$ is a scaled impulse response given by

$$h(x,y)=\frac{\sigma^2 f}{\sigma^2 f+\sigma^2 v}\delta(x,y) \tag{6}$$

$H(\omega_1,\omega_2)$ is derived under the assumption that pixel intensity $g(x,y)$ and noise value $n_G(x,y)$ are the samples of zero mean processes, so the current pixel value is updated by filtered value based on the local mean and variance as follows.

$$\hat{f}(x,y)=m_f(x,y)+\frac{\sigma^2{}_f(x,y)}{\sigma^2{}_f(x,y)+\sigma^2{}_v}(g(x,y)-m_f(x,y)) \tag{7}$$

Where $m_f(x,y)$ is the mean value of the window centered at (x,y), $\sigma^2 f(x,y)$ and $\sigma^2 v$ are the variance of local window and the variance of noise, respectively.

This method can be viewed as a special case of a two channel process. In the two channel process, the image to be processed is divided into two components, the local mean $m_f(x,y)$ and the local contrast $g(x,y)-m_f(x,y)$. If $\sigma^2 f(x,y)$ is much larger than $\sigma^2 v$ is the local contrast of $I(x,y)$ is assume primarily. On the other hand, the local contrast is significantly infected by the noise and the smooth process is performed by (7).

This adaptive wiener filter, which works well for removing gaussian noise, may diffuse the pollution of the impulse noise in the image. To solve this problem, the output of impulse noise detector in incorporated. The pixels in set NP are eliminated from the calculation of $m_f(x,y)$ and $\sigma^2 f(x,y)$. In this way, the adaptive wiener filter will not be applied to the impulse noise contaminated pixels. This is the main improvement of adaptive wiener filter for mixed gaussian noise and impulse noise.

2.3. Median Filter

The median filter is a simple rank selection filter that outputs the median of the pixels contained in its filtering window. The input-output relationship of the median filter may be defined as follows:

Let $x[r,c]$ denote the luminance value of the pixel at location (r,c) of the noisy input image. Here r and c are row and column indices, respectively, with $1 \le r \le R$ and $1 \le c \le C$ for an input image having a size of R-by-C pixels. Let $W_N[r,c]$ represent the group of pixels contained in a filtering window centered at location (r,c) of the noisy input image and having size of $(2N+1)-by-(2N+1)$ pixels.

$$W_N[r,c]=\{x[r+p,c+q] \| (p,q)=-N,..,N\} \tag{8}$$

Where N is a positive integer related with the size of the filtering window and p and q are integer indices each individually ranging from $-N$ to N.

The output of the median filter is equal to the median of the pixels contained in the filtering window $W_N[r,c]$

$$m[r,c] = Median(W_N[r,c]) \tag{9}$$

2.4. Edge Detector

Edges characterize boundaries and are therefore a problem of fundamental importance in image processing. Edges in images are areas with strong intensity contrasts – a jump in intensity from one pixel to the next. Edge detecting an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. The Canny edge detection algorithm is known to many as the optimal edge detector. The canny edge detection algorithm first smooths the image to eliminate the noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum (nonmaximum suppression). The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a non edge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above T2.

2.5. Neuro Fuzzy Network

The neuro fuzzy network used in the structure of the proposed hybrid filter acts like a fusion operator and attempts to construct an enhanced output image by combining the information from the noise filter, the edge detector and the noisy input image. The Neuro fuzzy network is a first order Sugeno type fuzzy system with three inputs and one output. Sugeno-type fuzzy systems are popular general nonlinear modeling tools because they are very suitable for tuning by optimization and they employ polynomial type output membership functions.

Let X_1, X_2, X_3 denote the inputs of the neural network and Y denote its output. Each noisy pixel is independently processed by the adaptive median and by adaptive Gaussian filter, Edge detector preserved the edges and being applied to the neural network as the second input. Hence, in the structure of the proposed operator, X_1 represents the output of the median/adaptive wiener filter for the noisy input pixel, X_2 represents the output of the edge detector for that noisy pixel, and X_3 represents the noisy pixel itself. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the neural network. Since the neural network has three inputs and each input has three membership functions, the rule base contains a total of 27 rules, which are as follows.

1) If (X_1 is M_{11}) and (X_2 is M_{21}), and (X_2 is M_{31}) then $R_1 = F_1(X_1, X_2, X_3)$.
2) If (X_1 is M_{11}) and (X_2 is M_{21}), and (X_1 is M_{32}) then $R_2 = F_2(X_1, X_2, X_3)$.
3) IF (X_1 is M_{11}) and (X_2 is M_{21}), and (X_1 is M_{33}) then $R_3 = F_3(X_1, X_2, X_3)$.
4) If (X_1 is M_{11}) and (X_2 is M_{22}), and (X_1 is M_{31}) then $R_4 = F_4(X_1, X_2, X_3)$.

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27) If (X_1 is M_{13}) and (X_2 is M_{23}), and (X_3 is M_{33}) then $R_{27} = F_3(X_1, X_2, X_3)$,

where M_{ij} where denotes the j th membership function of the i th input, R_k denotes the output of the k th rule, and F_k denotes the k th output membership function, with $i = 1,2,3$; $j = 1,2,3$; and $K = 1,2,3,...27$.

The *and* operator corresponds to the multiplication of input membership values. Hence, the weighting factors of the rules are calculated as follows:

$$w_1 = M_{11}(X_1).M_{21}(X_2).M_{31}(X_3)$$
$$w_2 = M_{11}(X_1).M_{21}(X_2).M_{32}(X_3)$$
$$w_3 = M_{11}(X_1).M_{21}(X_2).M_{33}(X_3)$$
$$\vdots$$
$$w_{27} = M_{13}(X_1).M_{23}(X_2).M_{33}(X_3)$$

Once the weighting factors are obtained, the output of the neural network can be found by calculating the weighted average of the individual rule outputs.

$$Y = \frac{\sum_{k=1}^{27} w_k R_k}{\sum_{k=1}^{27} w_k} \tag{10}$$

2.6. Training of the Neuro Fuzzy Network

The internal parameters of the neuro fuzzy network are optimized by training. During training phase, the overall goal is to determine the most accurate weights to be assigned to the connector lines. Also during training, the output is computed repeatedly and the result is compared to the preferred output generated by the training data. Here the parameters of the neuro fuzzy network are iteratively optimized so that its output converges to the output of the noise filter which completely removes the mixed noise from its input image. The ideal noise filter is conceptual only and does not necessarily exist in reality. It is only the output of the ideal noise filter is necessary for training, and this is represented by the original (noise-free) training image.

Although the density of the corrupting noise is not very critical regarding training performance, it is experimentally observed that the proposed operator exhibits the best filtering performance when the noise density of the noisy training image is equal to the noise density of the actual noisy input image to be restored. It is also observed that the performance of the proposed operator gradually decreases as the difference between the two noise densities increases. Hence, in order to obtain a stable filtering performance for a wide range of filtering noise densities, very low and very high values for training noise density should be avoided since it is usually impossible to know the actual noise density of a corrupted image in a real practical application. Results of extensive simulation experiments indicate that very good filtering performance is easily obtained for all kinds of images corrupted by impulse noise with a wide range of noise densities provided that the noisy training image has a noise density around 30%.

3. Experimental Results

The designed filter was tested using several noise conditions. The original image is corrupted by mixed noise. The filter was trained using original Lena image and the noise corrupted image. The values of MSE and PSNR (peak signal to noise ratio) of the proposed filter is compared to the other filters. The MSE, PSNR have been computed as

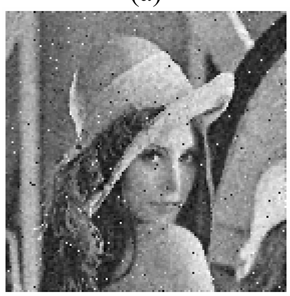
$$MSE=\frac{1}{N*M}\sum_{i=1}^{N}\sum_{j=1}^{M}(f^{\wedge}(x,y)-f(x,y))^{2} \tag{11}$$

$$PSNR=10\log_{10}\frac{255^{2}}{MSE} \tag{12}$$

Figure 4: **(a)** Original Lena image, **(b)** Lena image corrupted by Gaussian and Salt &Pepper noise, **(c)** Normal wiener filtering result, **(d)** Improved adaptive wiener filtering result, **(e)** Median filtering result, **(f)**Noise filtering result, **(g)** Result of the novel Hybrid filter.


(a)


(b)


(c)


(d)


(e)


(f)


(g)

The performance is tested at various noise densities and for different test images, and also compared with representative conventional as well as state-of-the-art impulse noise removal operators.

Table 2: Mean Square Error values for Several Filtering Methods

Noise Density %	Mean Square Error(MSE)						
	Noisy Image	Normal Wiener Filter	Improved Wiener Filter	Median Filter	Noise Filter	Existing Filter	Neuro Fuzzy Filter
1	0.0038	0.0039	0.0031	0.0030	0.0026	0.0029	0.0023
2	0.0158	0.0056	0.0035	0.0034	0.0027	0.0030	0.0025
3	0.0190	0.0072	0.0042	0.0040	0.0034	0.0033	0.0032
5	0.0221	0.0105	0.0060	0.0058	0.0050	0.0047	0.0045
10	0.0458	0.0199	0.0132	0.0137	0.0128	0.0120	0.0125
20	0.0955	0.0435	0.0349	0.0437	0.0408	0.0405	0.0401
30	0.1482	0.0671	0.0584	0.0918	0.0835	0.0840	0.0830
40	0.1987	0.0855	0.0779	0.1477	0.1325	0.1310	0.1305
50	0.2375	0.0933	0.0878	0.2028	0.1660	0.1650	0.1645

Table 3: Peak Signal to Noise Ratio values for Several Filtering Methods

Noise Density %	Peak Signal to Noise Ratio(PSNR) dB						
	Noisy Image	Normal Wiener Filter	Improved Wiener Filter	Median Filter	Noise Filter	Existing Filter	Neuro Fuzzy Filter
1	19.97	24.03	25.14	25.07	29.62	20.52	35.61
2	18.02	22.52	24.57	24.51	28.26	24.35	33.37
3	17.20	21.43	23.74	23.98	27.82	26.71	35.40
5	15.89	19.80	22.23	22.38	26.47	33.96	36.97
10	13.39	17.00	18.80	18.62	22.92	32.03	35.76
20	10.19	13.61	14.56	13.59	17.89	30.30	33.91
30	8.29	11.73	12.33	10.36	14.76	26.54	30.73
40	7.01	10.67	11.08	8.30	12.77	24.45	29.13
50	6.24	10.30	10.56	6.92	10.79	22.32	28.27

Experimental results show that the proposed operator yields superior performance over the competing operators cited in the paper and is capable of efficiently suppressing the noise in the image while at the same time effectively preserving thin lines, edges, fine details, and texture in the image.

4. Conclusion

A novel hybrid filtering operator for removing mixed noise from digital images is presented. The fundamental superiority of the proposed operator over most other operators is that it efficiently removes Gaussian and impulse noise from digital images while preserving thin lines and edges in the original image. A new noise filter design methodology is introduced for cancellation of mixed noise with the added feature of the preservation of edges. An efficient method for the detection of impulse noise pixels, an improved adaptive Wiener filter (based on the result of impulse noise detection) for removing Gaussian noise and a adaptive median filter for removing impulse noise are all contributed to this scheme to effectively eliminate both types of noise. Experimental results show that the proposed approach outperforms a number of existing algorithms and the improvement on detail preservation is significant.

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