X-RAY IMAGE GLOBAL ENHANCEMENT ALGORITHM IN MEDICAL IMAGE CLASSIFICATION

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Abstract. The current global enhancement algorithm for medical X-ray image has problems of poor de-noising and enhancement effect and low reduction of the enhanced medical X-ray image. To address the problems, a global enhancement algorithm for X-ray image in medical image classification is proposed in this paper. The medical X-ray image is gray scaled, which provides the basis for the further processing of the image. The noise in medical X-ray image is removed by using multi-wavelet transform to improve the enhancement effect of the method. With the curve-let domain the medical X-ray image is enhanced, the reduction degree of medical X-ray image is improved and the global enhancement of the medical X-ray image is completed. Experimental results show that the de-noising effect of the proposed method is effective, the enhanced medical X-ray image is better, and the reduction degree of medical X-ray image is high.

1. Introduction. With the rapid development of computer technology and digital technology, a large number of new imaging techniques have been applied to the medical field [20]. These technologies not only greatly enrich the field and level of diagnostic information, but also improve the level of diagnosis [7]. Since the introduction of computerized X-ray technology in 1980s, great changes have taken place in the field of X-ray imaging. CR not only provides image recognition and computer-aided, but also provides storage, digital transmission, etc., which not only solves the process of film processing, but also saves a lot of expenses [19, 22]. By the late 1990s, digital tablet technology appears. This technology uses X-ray image digital readout technology to realize the automation of X-ray detection. During the two exposures, there is no need to replace the film and store the fluorescent plate. Only a few seconds of data collection will be needed to observe the image [6, 17]. X-ray imaging is for displaying human structure information and is incorporated into the category of medical imaging [1]. Medical imaging plays a more and more important role in clinical diagnosis and teaching and research [5].
In traditional medical imaging diagnostics, the diagnosis of various diseases is mainly carried out by doctors' reading films. Therefore, the accuracy of judgment depends on the medical level and clinical diagnosis experience of the diagnostic doctor. There are many problems, such as the difficulty in quantitative measurement, the large individual difference and the strong subjectivity of the judgment results [8, 12]. To solve the above problems, the structure of the lesion is dissected by using computer for accurate positioning, enhancement, segmentation, quantitative analysis and processing, which can be used in medical image registration, reconstruction, surgical simulation, treatment planning, follow-up, computer assisted surgery technique [2,10]. By using medical image processing technology, the accuracy of clinical diagnosis can be greatly improved [13].

X-ray has strong penetration, and long X-ray radiation is harmful to the human body [24]. When the X-ray is used for the patient, an effective image should be generated at once to avoid repeated exposure [4]. However, the organization of the human body is very complex. The adverse effects such as electrical noise, light quantum noise and X-ray scattering in the imaging process results in the poor quality of the digital X-ray medical radiographic image [16, 18]. Compared with the general gray scale image, the contrast of medical X-ray image is poor and the details are more abundant. In addition, the dynamic range of medical X-ray images is also wide [11, 23]. If a doctor wants to make a correct diagnosis of the lesion, the image must be processed to improve the visual effect of the image [15, 21]. Due to the particularity of medical X-ray image, the image processing should avoid noise introduction, lose details of the image, and image detail distortion [3, 9]. The current medical X-ray image global enhancement algorithm has a poor denoising effect, the enhancement effect is not obvious, and the reduction degree of the enhanced image is low [14]. To address the above problem, a global enhancement algorithm for X-ray image in medical image classification is proposed in this paper.

2. Medical X-ray image preprocessing.

2.1. Representation of digital image. The image cannot be processed directly by a computer. It must be converted to a digital image before processing. An image can be expressed as an 2-D array \( f(x, y) \), where \( x \) and \( y \) is the coordinates in 2-D space \( XY \), \( f \) is the value of the point \((x, y)\). In order to be able to process medical X-ray images with a computer, it is necessary to discretize the coordinate space and the character space. The discretized image is a digital image. Each element in the image refers to an image element, called a pixel. The coordinates of \((x, y)\) represents the location of the pixel and \( f \) is sampled and quantized. After all the pixels are converted, the digital matrix is the object to be processed by the computer.

2.2. Gray scale of image. The commonly used image is gray scale image. \( f \) is the gray value, which represents the brightness of the corresponding point on the medical X-ray image. Brightness is the measure of reflection of the intensity of the object surface for the observer. The brightness function \( f(x, y) \) is larger than 0. The image is usually made up of light reflected from the target. Thus \( f(x, y) \) is composed of the amount of light incident on a visible scene and the ratio of the target to the incident light reflection, which are called as illumination component \( i(x, y) \) and reflection component \( r(x, y) \). \( f(x, y) \) is proportional to \( i(x, y) \) and \( r(x, y) \), which is expressed as
\[ f(x, y) = i(x, y) \times r(x, y) \]  

The function \( f(x, y) \) is called as gray scale. The energy of the incident light on the surface of an object is limited and is always positive, that is, \( 0 < r(x, y) < \infty \).

When the reflection coefficient is 0, it means all the light is absorbed by the object. When the reflection coefficient is 1, it means that all the light is reflected by the object, and the reflection coefficient is between the total absorption and the total reflection, that is, \( 0 < r(x, y) < 1 \). Therefore, the gray value of the image is also nonnegative and bounded.

\( l \) denotes the gray scale of the medical X-ray image, then \( L_{\text{min}} \leq l \leq L_{\text{max}} \), where

\[ L_{\text{min}} = i_{\text{min}}r_{\text{min}} \tag{2} \]
\[ L_{\text{max}} = i_{\text{max}}r_{\text{max}} \tag{3} \]

\( L_{\text{min}} \) and \( L_{\text{max}} \) is the lower limit and upper limit of the image gray values. The limitation is that \( L_{\text{min}} \) is positive and \( L_{\text{min}} \) is limited. The interval \([L_{\text{min}}, L_{\text{max}}]\) refers to gray scale range. For the convenience of representation, the gray scale image is usually normalized. \( 0 \) represents the gray scale of black and \( L \) represents the gray scale of white. The median value represents the gray value from black to white, that is \( 0 \leq l \leq L \). The normalization is \( 0 \leq l \leq 1 \), where 0 is the most black and 1 is the most white. Therefore, an image of brightness distribution can be finally expressed as a two-dimensional gray variable function of the coordinate point \((x, y)\) in a plane coordinate system.

2.3. Gray histogram. Gray histogram is the simplest and most useful tool in digital image processing. It reflects the statistical relationship between gray level and the occurrence frequency in medical X-ray image. It can change gray scale distribution of the histogram to make the gray scale evenly in the whole gray range space, so the effect of image enhancement is achieved.

Gray histogram can also be represented by the relative frequency of each gray value (the ratio of the number of pixels with this gray scale to the total number of pixels of the image), which is given by

\[ p(r_k) = \frac{n_k}{n} \quad k = 0, 1, \ldots, L - 1 \tag{4} \]

where \( r_k \) is the \( k \)th gray level, \( n_k \) is the number of the pixels with the appearance of \( r_k \), \( p(r_k) \) is the probability of the appearance of gray level \( r_k \).

Assume a continuous image \( D(x, y) \). It changes smoothly from the high gray level of the center to the low level of the edge. A gray level \( D_1 \) is selected to define a contour line, which connects all the points of gray level \( D_1 \) in the image. The obtained contour line forms a closed curve that surrounds the gray level greater than the \( D_1 \) region. The higher gray level \( D_2 \) is to form the second contour line. Assume \( A_1 \) is the area of the region surrounded by the first contour line, \( A_2 \) is by the second contour line, as shown in Fig. 1.

The area of the region surrounded by all the contour line with gray level \( D \) in a continuous image is called threshold area function \( A(D) \), and the histogram is defined by

\[ H(D) = \lim_{\Delta D \to 0} \frac{A(D) - A(D + \Delta D)}{\Delta D} = - \frac{d}{dD} A(D) \tag{5} \]

It can be concluded that the histogram of a continuous image is the negative value of the derivative of the area function. The minus is due to \( A(D) \) decreases
with the increase of $D$. If the image is regarded as a two-dimensional random variable, the area function is equivalent to the cumulative distribution function, and the gray histogram is equivalent to its probability density function.

For the discrete function, $\Delta D$ is set to 1, then

$$H(D) = A(D) - A(D + 1) \quad (6)$$

If all the gray levels are concentrated in a very small range, the dynamic range of the image gray value is very small, and the corresponding image contrast is low. If all the gray levels are evenly distributed in the larger range, the corresponding image has a larger contrast. The gray histogram gives a general overview on image description, for example, gray range of the image, appearance frequency of each gray level, gray level distribution, and average brightness and contrast, which provides an important basis for the further processing of medical X-ray image.

2.4. Medical X-ray image denoising method based on multi-wavelet transform. The multi-wavelet transform is different from the single wavelet transform. Pre-filtering is required before transformation. Pre-filtering is designed to eliminate the improper discreteness of multi-wavelet. After pre-filtering, the corresponding wavelet transforms are carried out. In the same way, after the reconstruction of multiple wavelets, the complete multi-wavelet reconstruction can be achieved by the post-filtering.

Multi-wavelet is generated by the scale function $\{\phi_k(x)\}_{1 \leq k \leq r} \in L^2(R)$ with $r \geq 2$ and the corresponding wavelet function $\{\psi_k(x)\}_{1 \leq k \leq r} \in L^2(R)$ with dilation and translation. Assume $\{H_k\}_{1 \leq k \leq L-1}$ and $\{G_k\}_{1 \leq k \leq L-1}$ is $r \times r$ filter matrix, $\Phi(x) = \{\varphi_1(x), \varphi_2(x), \ldots, \varphi_r(x)\}^T$ and $\Psi(x) = \{\psi_1(x), \psi_2(x), \ldots, \psi_r(x)\}^T$ is the scale function vector and wavelet function, respectively. Multi-wavelet transform is expressed as

$$\Phi(x) = 2 \sum_{k=0}^{L-1} H_k \Phi(2x - k) \quad (7)$$

$$\Psi(x) = 2 \sum_{k=0}^{L-1} G_k \Phi(2x - k) \quad (8)$$
where $H_k$ and $G_k$ are $r \times r$ matrixes, which is called matrix scale coefficient of double scaling equations, or matrix filter coefficient. The decomposition and reconstruction of Mallat algorithm in orthogonal single wavelet is extended to orthogonal multi-wavelet, and the decomposition of multi-wavelet can be obtained by

$$C_{j-1} = \sqrt{2} \sum_{n \in \mathbb{Z}} h_{n-2k} C_{j,n}, k \in \mathbb{Z}$$

$$D_{j-1} = \sqrt{2} \sum_{n \in \mathbb{Z}} g_{n-2k} C_{j,n}, k \in \mathbb{Z}$$

Reconstruction of multi-wavelet is given by

$$C_{j,k} = \sqrt{2} \sum_{n \in \mathbb{Z}} h^*_{n-2k} C_{j,n} + g^*_{n-2k} D_{j-1,n}$$

where $C_{j,k} = [c_{0,j,k}, \ldots, c_{r-1,j,k}]^T$, $D_{j,k} = [d_{0,j,k}, \ldots, d_{r-1,j,k}]^T$, $h^*_n$ and $g^*_n$ is the conjugate transpose of $h_n$ and $g_n$.

Assume the signal to be processed is $x(m,n), m, n \in \mathbb{Z}, 1 \leq m \leq M, 1 \leq n \leq N$. After preprocessing, 4 components with $m/2 \times n/2$ are generated, which are $C_{11}, C_{12}, C_{21}, C_{22}$. Multi-wavelet transform for the four components is to generate 16 components with $m/4 \times n/4$, which is given by

$$M_w = \begin{pmatrix}
C_{LL1} & C_{LL2} & C_{HL1} & C_{HL2} \\
C_{LL3} & C_{LL4} & C_{HL3} & C_{HL4} \\
C_{LH1} & C_{LH2} & C_{HH1} & C_{HH2} \\
C_{LH3} & C_{LH4} & C_{HH3} & C_{HH4}
\end{pmatrix}$$

The total pixel of the X-ray image in the whole transformation process remains unchanged, and the system block diagram of the multi-wavelet decomposition and reconstruction is shown in Fig. 2.

In Fig. 2, $H(\omega)G(\omega)$ is multi-wavelet filter, $\tilde{H}(\omega)\tilde{G}(\omega)$ is multi-wavelet inverse filter, $Q(\omega)$ and $\tilde{Q}(\omega)$ is pre-filter and post-filter, respectively.

The design of the multi-wavelet filter used in this paper is transformed into the design of low pass filter and high pass filter. Multi-wavelet pre-filter and post-filter

\[x(m,n)\xrightarrow{Q(\omega)} C_{11} \xrightarrow{C_{12}} H(\omega)G(\omega) \xrightarrow{M_w} \]

\[x(m,n)\xrightarrow{\tilde{Q}(\omega)} C_{11} \xrightarrow{C_{12}} \tilde{H}(\omega)\tilde{G}(\omega) \xrightarrow{\tilde{M}_w}\]

**Figure 2.** System structure of multi-wavelet decomposition and reconstruction
are given by

\[
\begin{align*}
\text{Pr}e(0) &= \begin{bmatrix} 3/8\sqrt{2} & 10/8\sqrt{2} \\ 0 & 0 \end{bmatrix}, \quad \text{Pr}e(1) = \begin{bmatrix} 3/8\sqrt{2} & 0 \\ 1 & 0 \end{bmatrix} \\
\text{Post}(1) &= \begin{bmatrix} 0 & 1 \\ 0 & -3/10 \end{bmatrix}, \quad \text{Post}(0) = \begin{bmatrix} 0 & 4\sqrt{2/5} \\ 1 & 3/10 \end{bmatrix}
\end{align*}
\]

Multi-wavelet is used for denoising, and the filters are given by

\[
\begin{align*}
L(0) &= \begin{bmatrix} 3/5\sqrt{2} & 4/5 \\ -1/20 & -3/10\sqrt{2} \end{bmatrix}, \quad L(1) = \begin{bmatrix} 3/5\sqrt{2} & 0 \\ 9/20 & 1/20 \end{bmatrix} \\
L(2) &= \begin{bmatrix} 0 & 0 \\ 9/20 & -3/10\sqrt{2} \end{bmatrix}, \quad L(3) = \begin{bmatrix} 0 & 0 \\ -1/20 & 0 \end{bmatrix} \\
H(0) &= \begin{bmatrix} -1/20 & -3/10\sqrt{2} \\ 1/10\sqrt{2} & 3/10 \end{bmatrix}, \quad H(1) = \begin{bmatrix} 9/20 & -1/\sqrt{2} \\ 9/10\sqrt{2} & 0 \end{bmatrix} \\
H(2) &= \begin{bmatrix} 9/20 & -3/10\sqrt{2} \\ 9/10\sqrt{2} & -3/10 \end{bmatrix}, \quad H(3) = \begin{bmatrix} -1/20 & 0 \\ -1/10\sqrt{2} & 0 \end{bmatrix}
\end{align*}
\]

3. Global enhancement algorithm for medical X-ray image. According to the enhancement processing of medical X-ray image based on curvelet domain, the algorithm mainly consists of 3 steps: image edge direction feature extraction in curvelet domain, edge feature curvelet coefficient location and edge feature curvelet coefficient enhancement.

3.1. Curvelet domain edge feature extraction of medical X-ray image. Select the curvelet coefficient on 1 or more scale layers. Assume transform on \( P \) scales \( \{j_1, j_2, \ldots, j_p\}, j_p \) is the highest layer of \( P \) scales. The range of \( k \) in \( C\{j_i\} \) is \( K_{i,1} \times K_{i,2}(0 \leq k_1 < K_{i,1}, 0 \leq k_2 < K_{i,2}) \). The range of \( k \) in \( C\{j_p\} \) is \( G_p : K_p,1 \times K_p,2 \). The direction field is calculated on the \( j_p \) layer. The coefficient in the coarser scale \( C\{j_i\}(i = 1, 2, \ldots, P - 1) \) is mapped to \( j_p \). The mapping includes the mapping of the direction parameter \( l \) and position parameter \( k \).

Assume the number of the direction variables in the \( j_i \) layer is \( L_i \). The set of the mapping of each direction variable to the \( j_p \) layer is denoted as \( D_{i,p}(l) \), which is given by

\[
D_{i,p}(l) = \left\{ l' \in [0, 1, 2, \ldots, L_p - 1] \mid l \leq \frac{l'}{L_p} l_i < l + 1 \right\}
\]

where \( L_p \) is the number of the direction variables in the \( j_p \) layer. The parameter set of the mapping of \( C\{j\}\{l\}(k) \) to the translation position in the \( j_p \) layer is denoted as \( A_{i,j_p}(k) \), which is given by

\[
A_{i,j_p}(k) = \left\{ (k'_1, k'_2) \in G_p | k_d - 0.5 \leq \frac{k'_d}{K_{p,d}} K_{i,d} < k_d + 0.5 d, d = 1, 2 \right\}
\]

In this way, \( C\{j\}\{l\}(k) \), \( j = j_1, j_2, \ldots, j_{p - 1} \) is mapped to the \( j_p \) layer. For each direction \( l \) and the translation position \( k = (k_1, k_2) \) in the \( j_p \) layer, the sum of the amplitude of all the corresponding curvelet coefficients is denoted as \( M_{i, k} \) and

\[
M_{i,k} = \sum_{i=1}^{p} \sum_{l' \in D_{i,p}(l)} \sum_{k' \in A_{i,j_p}(k)} |C\{j_i\}\{l'\}(k')|, \quad \left( l = 0, 1, \ldots, \frac{L_p}{2} - 1; k \in G_p \right)
\]
As the difference between the direction parameter $l$ and the angle expressed by $l + \theta_l$ is $180^\circ$, it is considered that they represent the same characteristics. When the curvelet coefficient is complex, $|C \{ j \} \{ l \}| = |C \{ j \} \{ l + L_j/2 \}|$. Then only $L_j/2$ directions can be calculated.

After direction mapping and position mapping, each displacement parameter $k$ corresponds to $L_j$ amplitude values $M_{l,k}$. The direction $l$ of the maximum amplitude values $M_k$ is the main direction $l_0(k)$, which is given by

$$l_0(k) = \arg \max_{l=0,1,\ldots,L_j/2^{-1}} M_{lk}$$

(19)

In this way, the 2 components at each translation position $k$ in the $j_p$ layer are obtained and denoted as $\Psi(k) = (M_k,l_0k)$. $\Psi$ is defined as edge direction feature in curvelet domain. The amplitude component $M_k$ represents the strength of the edge, and the direction component $l_0k$ represents the direction of the edge.

3.2. Edge feature curvelet coefficient location of medical X-ray image. Assume the threshold of the amplitude component $M_k$ is $\text{thresh}$. The translation position of the feature curvelet coefficient is determined by

$$k' = \{ k' \in G_p | M'_k > \text{thresh} \}$$

(20)

From the definition of curvelet transform and physical meaning, it can be known that, the curvelet coefficient of the specific directional subband $l$ represents the edge feature in the specific direction $\theta_l$. There exists quantitative relationship between $l$ and $\theta_l$. According to the direction $l_0k$ of $\Psi(k)$, the edge direction $\theta_l$ can be calculated. Through setting the angle range of the edge direction, the curvelet coefficient of the specific directional subband can be enhanced and the edge feature is also enhanced. Assume the angle range of the edge direction is $\theta_{\text{range}}$, combined with Eq. (16) and Eq. (17), the translation position $\hat{k}$ and subband position $l_0_k$ of the edge feature curvelet coefficient is given by

$$\hat{k} = \{ k \in G_p, M_{\hat{k}} > \text{thresh} & \theta_{l_0k} \in \theta_{\text{range}} \}$$

(21)

Then the feature curvelet coefficient of each layer $C \{ j \} \{ l_0j \} \{ \hat{k}_j \}, (j = j_1,j_2,\ldots,j_p)$ is obtained.

3.3. Edge feature curvelet coefficient enhancement of medical X-ray image. The extracted feature curvelet coefficient $C' \{ j \} \{ l_0j \} \{ \hat{k}_j \}$ is enhanced by

$$C' \{ j \} \{ l_0j \} \{ \hat{k}_j \} = \lambda_{\hat{k}_j} \times C \{ j \} \{ l_0j \} \{ \hat{k}_j \}$$

(22)

$$C' \{ j \} \{ l_0j + L_j/2 \} \{ \hat{k}_j \} = \lambda_{\hat{k}_j} \times C \{ j \} \{ l_0j + L_j/2 \} \{ \hat{k}_j \}$$

(23)

where $L_j$ is the number of the direction subband of the $j$th scale layer, $C \{ j \}$ and $C \{ j + L_j/2 \}$ represent the edge features of the same direction in the image. The selection of the enhancement factor $\lambda_{\hat{k}_j}$ directly determines the visual effect of the enhanced medical X-ray image. The enhancement factor is constructed by using

$$\lambda_{\hat{k}_j} = \min \left[ A \times \left( \frac{\max |C \{ j \} \{ l_0j \}|}{C \{ j \} \{ l_0j \}} \right)^{s}, \frac{\max |C \{ j \}|}{C \{ j \}} \right]$$

(24)
where $A$ is the gain constant, $S$ is the nonlinear factor, $C\{j\}\{l_{0j}\}(\hat{k}_j)$ is the amplitude of feature curvelet coefficient to be enhanced, $\max|C\{j\}\{l_{0j}\}|$ is the maximum amplitude of the subband coefficient $C\{j\}\{l_{0j}\}$, $\max|C\{j\}|$ is the maximum amplitude of all the curvelet coefficient with the $j$th scale. The introduction of $\max|C\{j\}|/C\{j\}\{l_{0j}\}(\hat{k}_j)$ is to prevent the excessive value of $A$ or $S$ to destroy the overall gray level of medical X-ray image, that is $\lambda_{\hat{k}_j} \leq \max|C\{j\}|/C\{j\}\{l_{0j}\}(\hat{k}_j)$.

4. Experimental results and analysis. The performance test is carried out to verify the proposed global enhancement algorithm for medical X-ray image. In the experiment, the operating system is Windows7 and the platform is matlab7.0. Medical X-ray image global enhancement algorithm, image enhancement algorithm based on Retinex theory, and image enhancement algorithm based on double plateaus histogram are used for test, respectively. The denoising effect of the three methods is compared and the test results are shown in Fig. 3.

From Fig. 3(b), it can be seen that, the processed image is more blurred than the original image. The enhancement effect is not obvious, the edge is not clear.
enough, and the contrast is weaker, which is not conducive to the needs of visual observation and diagnosis. From Fig. 3(c), it can be seen that, after processing, the edge detail is more prominent, but the image is too bright and the contrast is not strong, it is not easy to observe for the human eye, and the noise is obvious. From Fig. 3(d), it can be seen that, after processing, the edge detail is clear, the noise is relatively small, and the contrast is large, it is convenient for visual observation and diagnosis. The effect is better than the other algorithms.

The global enhancement of medical X-ray image may result in image distortion. The output image will be different from the original image to some extent. In order to measure the processed medical X-ray image quality, the PSNR value is tested. The greater the PSNR value represents the less distortion of medical X-ray image after enhancement processing. The unit of PSNR is dB and the computation is given by

\[
PSNR = 10 \times \log_{10} \left( \frac{(2^n - 1)^2}{MSE} \right)
\]  

where MSE represents the \(n\)th pixel value of the original image. The smaller the value of MSE, the greater the value of PSNR, the less the distortion. The obtained PSNR value and MSE value are shown in Table 1.

In order to express more intuitively, the data in Table 1 is plotted in Fig. 4.

From Fig. 4 and Table 1, the MSE value of the proposed algorithm is less than other algorithms and the PSNR value of the proposed algorithm is higher than other algorithms. It proves that X-ray image global enhancement algorithm in medical image classification is less distorted and the enhancement effect is good.

Medical X-ray image is the basis for a doctor to make a diagnosis. The degree of image reduction after enhanced with three different methods is compared and the test results are shown in Fig. 5.

From Fig. 5(a), it can be known that, the reduction degree of medical X-ray image is more than 70% by using the global enhancement algorithm of X-ray image

| Number of iterations | PSNR/dB | MSE/dp |
|----------------------|---------|--------|
|                      | The proposed method | Retinex-based method | Double plateaus histogram-based method | The proposed method | Retinex-based method | Double plateaus histogram-based method |
| 1                    | 18.9672 | 13.2654 | 11.6587 | 824.839 | 965.325 | 978.547 |
| 2                    | 18.9658 | 13.6548 | 12.3689 | 823.657 | 942.354 | 968.348 |
| 3                    | 19.5781 | 12.6849 | 11.3589 | 836.348 | 951.347 | 946.256 |
| 4                    | 19.6875 | 13.6528 | 10.3647 | 846.268 | 912.487 | 925.645 |
| 5                    | 18.6597 | 11.3549 | 12.0367 | 851.267 | 937.985 | 971.648 |
| 6                    | 20.3698 | 12.4872 | 9.2657  | 865.215 | 978.654 | 985.157 |
| 7                    | 21.8571 | 11.8627 | 9.5489  | 836.259 | 996.125 | 977.627 |
| 8                    | 24.6257 | 10.6894 | 12.3647 | 841.025 | 984.367 | 955.348 |
| 9                    | 23.1459 | 10.8547 | 10.3658 | 823.024 | 971.254 | 957.518 |
| 10                   | 22.6587 | 9.3657  | 9.6581  | 856.237 | 956.185 | 975.264 |
Figure 4. PSNR values of three methods.
Figure 5. Degree of reduction of three methods
in medical image classification. From Fig. 5(b), it can be known that, the reduction degree of medical X-ray image is less than 70% by using the enhancement algorithm based on Retinex theory. From Fig. 5(c), it can be known that, the reduction degree of medical X-ray image is less than 70% by using the enhancement algorithm based on double plateaus histogram. Comparison results show that, the reduction degree obtained with the proposed algorithm is higher than other two algorithms.

5. Conclusions. X-ray imaging is an imaging method for displaying the information of human body structure, which is included in the category of medical imaging. The role of medical imaging in clinical diagnosis and teaching and scientific research is becoming more and more important. With the current medical X-ray image global enhancement algorithm, the denoising effect is poor, the enhancement effect is not obvious, and the degree of reduction is low. In this paper, X-ray image global enhancement algorithm in medical image classification is proposed. The denoising effect is good and the enhancement effect is obvious. The enhanced medical X-ray image has a high degree of reduction, which can provide the basis for diagnosis of the doctor.

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