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Image Contrast Enhancement Algorithm Based on GM(1,1) and Power Exponential Dynamic Decision

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Image enhancement processing is a very important operation during image preprocessing. Compared with to enhancc the overall contrast level of image, enhancing the local contrast of image can improve the level of such contrast directly as well as the quality and effect of image enhancement. In this paper, the gray prediction model is applied to the process of enhancing image local contrast, so as to measure the change range of image local contrast and adaptively adjust the scale of enhancing image local contrast. The simulation results show that, in addition to enhancing the contrast of gray level on the edge of image, the proposed algorithm can inhibit roughened nonedge region and improve the quality of local enhancement processing, which create a more favorable condition for the further image edge detection.

Keywords: Contrast enhancement; gray prediction model; image processing.

1. Introduction

Image enhancement is actually a very broad concept. It refers to removing bad components from the image, such as noise, impurities, etc., in order to retain and enhance the original composition of the image, so that the image quality could be more in line with human visual characteristics or machine identification requirements. If denoising or filtering is a must-have for a poor quality image, to adjust grayscale or increase local contrast of the suboptimal image, which quality is not very bad or noise problem has been improved, it will undoubtedly give us better visual enjoyment or machine identification quality.

Here, we first introduce the methods of enhancing the overall gray level of image. The most common methods include direct grayscale transformation, histogram equalization, contrast enhancement, histogram specification as well as high-pass filtering, low-pass filtering, band-pass, band-stop filtering and so on.[18,21] Whether it is spatial enhancement or frequency domain enhancement, their common feature is that the specifically processed object is all pixels with same gray value or at same frequency in the whole image. While the local enhancement is to adjust the grayscale of a local area (usually using 3×3 window neighborhood) in the image, that is to say, only a block of the whole image is chosen to be enhanced. The visual perception on the image is not only related to the overall gray level of pixel, but also to the pixel gray level distribution of the neighborhood of image. According to human eyes, the pixels with the same grayscale value are distinct in different neighborhoods, so improving the image contrast will have a positive effect on improving the quality of image.

At present, enhancing the local contrast[8,12] of image mainly involves the regions with less contrast or even without enlarging its contrast intensity, while the region with greater local contrast is enhanced to a more substantial degree. Thus, the edges of high frequency component in the image can be sharpened, making it easier to detect and extract edges in the next step.

In the image processing, when the target information in three-dimensional space is mapped to a two-dimensional plane, the existence of information missing itself would cause some ambiguity, and the definition of image edge, the texture and other features will be ambiguous. Besides, the interpretation of the underlying processing of image inevitably has a fuzzy phenomenon. Therefore, the application of fuzzy mathematics used "for solving the problem of cognitive uncertainty" in the image processing has a certain degree of adaptability.[10,19,22,23]

However, due to the complexity of image texture, the diversity of image noise and the less data after the image is heavily polluted, the determination of membership function in the fuzzy enhancement algorithm of image lacks the support of some prior experience. All these will cause a certain degree of obstacles called "extension quantification". It can be seen that merely using fuzzy mathematics to deal with image processing problems cannot achieve the desired results. Gray system theory is based on the gray obscure set, proposed mainly for the "lack of data, but also lack of experience" problems with uncertainty, and provides a tool and approach in order to solve the image enhancement problem.

In general, images are inevitably led to missing or mutated information in the process of acquisition, transmission and storage. Therefore, the general image is an incomplete image lacking real information to a certain degree. This is in line with the advantages of gray system theory, which is featured by good at dealing with uncertainty problems that "some information is known, while some information is unknown",[3] or "less sample, poorer information".[3] So, we think that the image has typical gray features, and gray properties of the image are very important features therein. Various subjective and objective reasons result in the loss of effective data in image and the obfuscation of edge within nonedge region, in which both increase the grayness of the image.

"The essence of gray system theory is 'less' and 'uncertain' ".[3] The "little data" feature coincides with the reality that the amount of data in image cannot be too big in the process of acquiring and real-time processing, because the capacity of image processing system is limited, and massive data can only cause a reduced processing efficiency and increased cost that is not allowed by the reality. "Uncertainty" is just the same as that the image data distribution law is unknown and easy to be polluted by noise, the process of imaging has geometric distortion, and some noise pixels and edge pixels belong to low gray level pixels and are quite difficult to identify. These two salient features are the inherent nature of gray system theory, which cannot be achieved by other uncertainty theories.

The enhancement of image is to sharpen the edge portion of image and dilute the smooth portion of image, and the grayscale contrast between the image target area and background area is appropriately enlarged, in order to facilitate automatic identification on the edge by machine. However, the grayscale contrast of image local area should not be too large, so as to avoid gray overshoot. Therefore, in the image contrast enhancement process, how to grasp the enhancing degree is uncertain. Thus, it is appropriate to use the gray system theory to solve the image processing problem.

Gray prediction model (GM(1,1)) is a very important model in gray system theory.[3] There are some literatures[13] on the application of gray prediction model in image edge detection.[14,24,28] As the gray prediction model has achieved good results in image edge detection, and the correlation between image contrast enhancement and edge detection is used, so we consider to use gray prediction model in image contrast enhancement. But such examples are still relatively rare. Compared with the gray relational analysis theory,[9] the application of gray prediction model in image processing is much less than that of gray relational degree in image processing.[5] The reason is that the gray prediction model is more stringent to the modeling data, and many occasions are not suitable to use gray prediction model for modeling. Therefore, we need to overcome the weakness that the original data for gray prediction model needs to meet very strict modeling conditions, try to search for a coherence point between gray prediction model and image enhancement, and finally solve the image enhancement problems with gray prediction model.

2. Introduction to Gray Prediction Model

Gray prediction model is the core content and classic part of gray system theory. Since the gray system theory was born, the gray prediction theory has aroused the broad interest of scholars and experts. In contrast to the traditional regression prediction model, the gray prediction model can achieve better accuracy in the case of less data (generally considered to be at least four sample data) and poor information modeling, overcoming the shortcomings of traditional statistical methods that require high-volume sample databases.

The gray prediction model is based on the fact that it is generated by the accumulation of original sequence, so that a gray system contains the exponential law to be presented. By using the discrete approximation of primary differential equation, a discrete gray prediction model with parameters is established. The least squares method is used to estimate these parameters. Then, new sequences are deduced and the approximate sequences of original sequences are obtained. Finally, the results of accuracy test are verified and the predicted sequence can be obtained by extending the time for fitted formula which meets the precision control requirements.

In the gray prediction model, the most classic model is GM(1,1) model.[3]

Definition 1 ([3]). Let the original sequence be a nonnegative sequence,

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)). \tag{1}$$

$X^{(1)}$ is a cumulative generation sequence of $X^{(0)}$,

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)), \tag{2}$$

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) = x^{(1)}(k-1) + x^{(0)}(k),\ k = 1, 2, \ldots, n$. $Z^{(1)}$ (or background value) is the mean sequence generated by consecutive neighbors of $X^{(1)}$,

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)), \tag{3}$$

where $z^{(1)}(k) = 0.5(x^{(1)}(k) + x^{(1)}(k-1)), k = 2, 3, \ldots, n$. We call

$$x^{(0)}(k) + az^{(1)}(k) = b, \tag{4}$$

GM(1,1) model, the corresponding approximate differential equation $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ is the whitening equation (or shadow equation) of GM(1,1) model $x^{(0)}(k) + az^{(1)}(k) = b$.

Theorem 1 ([3]). *Let*

$$P = \begin{bmatrix} a \\ b \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \quad B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}.$$

By the least squares estimation parameter method, the parameter column of GM(1,1) *model* $x^{(0)}(k) + az^{(1)}(k) = b$ *satisfies*

$$P = (B^T B)^{-1} B^T Y. \tag{5}$$

Theorem 2 ([3]). *Let* P, Y, B *be described as in Theorem* 1, *then*

(1) *the solution of the whitening equation* $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ *is*

$$x^{(1)}(t) = \left(x^{(1)}(1) - \frac{b}{a}\right)e^{-at} + \frac{b}{a}, \tag{6}$$

(2) *the time response sequence of* GM(1,1) *model* $x^{(0)}(k) + az^{(1)}(k) = b$ *is*

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \quad k = 1, 2, \ldots, n, \tag{7}$$

(3) *the restore value of the original sequence is*

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1-e^{a})\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak}, \quad k = 1, 2, \ldots, n, \tag{8}$$

where parameter $-a$ is called the development coefficient, reflecting a development trend of the sequence, that is, when the speed of the curve changes, b, called the gray effect, is extracted from the background value of the data, reflecting the relationship between the changes in data, which is a concrete manifestation of the extension of connotation.

Gray prediction model is an important part of gray system theory and a very useful concept and method in forecasting theory. The application of gray prediction model in image filtering or enhancement was an effective new attempt at the beginning of this century.

In filtering the image, we mainly use the gray prediction theory to fit and predict the original sequence of image data whose gray values fluctuate little, and the gray value of the noise point usually has very intense mutation compared with normal pixel. So, by selecting reasonable data, we can mask the gray value of the mutation. Although the edge of image will still display a certain degree of mutation on the gray value of pixels, neither as the noise point so violent, nor as the noise point being without continuity in the texture. So, the biggest difference between the edge and noise is that the edge generally shows a direction of continuity but not noise.

The traditional image fuzzy enhancement algorithms include PAL and King's fuzzy enhancement algorithm[20] and fuzzy contrast enhancement algorithm. The two kinds of algorithms illustrate image enhancement from different perspectives: Pal and King's fuzzy enhancement algorithm is to find a reasonable threshold for separating target and background from the overall grayscale of image pixel (by the largest interclass variance method, a typical approach), then increase the pixel gray value greater than the threshold value, and reduce the pixel gray value smaller than the threshold, thereby increasing the contrast of image as a whole. In this algorithm, we do not correlate with the specific texture distribution of image pixels by counting the overall grayscale value of each gray level of the image. So, this practice does not actually use the local texture pixel distribution information of the image, and for the image with the atypical bimodal histogram, it generally cannot achieve better results. The image enhancement algorithm corresponding to the fuzzy contrast can focus on enhancing the local texture information of image, which enlarges the contrast of image edge by enlarging the difference between the gray value of central pixel and the mean value of pixels of its neighborhood of the image. The result is that the local enhancement of image is very good, but the lack of statistical analysis on the overall gray value of image is considered. In this paper, the neighborhood pixel gray value is used to predict the intensity of contrast enhancement of the image adaptively, and good results are obtained.

3. Traditional Image Contrast Enhancement Algorithm

Someone put forward an improved image denoising algorithm based on gray prediction model.[25] In Ref. 6, they designed a very useful gray model filter, and in Ref. 26, the gray prediction model was applied to the image denoising algorithm. Compared with traditional mean filtering and median filtering methods, the new algorithm can achieve a better effect on removing salt and pepper noise. In Refs. 11 and 27, the gray prediction model is applied to the image edge detection. Gray prediction model used in the edge region of image will have a greater error, while in the smooth region of the image, this error is relatively small. In a variety of image enhancement algorithms, Beghdadi[1] proposed an image contrast enhancement algorithm based on local edge decision, which improved the algorithm based on the definition of local contrast.[4] In order to be able to calculate the average edge value, they used the gradient operator to detect the edge, such as Sobel operator, Laplacian operator. In addition to the gradient operator, some scholars have also proposed the "Teagle–Kaiser Energy Operator (2DTKEO)",[2] known as the "Teager–Kaiser" contrast enhancement. Noting that the human visual mechanism is relatively more sensitive to the image contour, Beghdadi[1] proposed an edge detection operator to construct the definition of local contrast, which can be described as follows[7]:

$$C_{kl} = |X_{kl} - \overline{E}_{kl}| / |X_{kl} - \overline{E}_{kl}|, \tag{9}$$

$$\overline{E}_{kl} = \left(\sum_{(i,j)\in W_{kl}} \Delta_{ij} \bullet X_{ij} \right) \bigg/ \left(\sum_{(i,j)\in W_{kl}} \Delta_{ij} \right), \tag{10}$$

where X_{kl} represents the gray value of the center point of window W_{kl}, and X_{ij} represents the gray value of the center point of window W_{ij} corresponding to the edge detection operator. ($W_{kl} = \{X_{ij} | k-1 \le i \le k+1, l-1 \le j \le l+1\}$. Two windows W_{kl} and W_{ij} are different.)

$\overline{E}_{kl}$ represents the local average edge value of the neighborhood window W_{kl}. Δ_{ij} represents the edge intensity information at the location (i,j), which can be calculated by the Laplacian operator and the Sobel operator. In Refs. 1 and 7, it can be given by Laplacian operator.

$$\Delta_{ij} = |X_{ij} - \overline{X}|, \tag{11}$$

where $\overline{X} = (X_{i+1,j} + X_{i-1,j} + X_{i,j+1} + X_{i,j-1})/4$.

Adjust the contrast function, so that its contrast value can be larger than before.

$$F(C_{kl}) = (C_{kl})^{a/b}, \tag{12}$$

where a and b meet the conditions $0 < a < b$, $b = 2^p$, and p is an integer.

$$C'_{kl} = F(C_{kl}), \tag{13}$$

where $C_{kl} \in [0, 1]$, $F(C_{kl}) > C_{kl}$, and $F(C_{kl}) \in [0, 1]$.

The enhanced pixel gray values can be derived from Eq. (9) of local contrast:

$$X'_{kl} = \begin{cases} \overline{E}_{kl}(1 - C'_{kl})/(1 + C'_{kl}), & X_{kl} \le \overline{E}_{kl}, \\ \overline{E}_{kl}(1 + C'_{kl})/(1 - C'_{kl}), & X_{kl} > \overline{E}_{kl}. \end{cases} \tag{14}$$

Here, they gave the definition of local contrast, and by using the edge detection operator, through constructing a local contrast function, they got a better implementation effect. However, it also has some shortcomings. It increases the contrast of image edge, and also blindly increases the contrast of smooth area in the image, making the image to become rough. At the same time, the overall enhancement effect is not satisfactory.

Recognizing the shortcomings of classical methods, we can easily analyze its reason, that is, it uses Laplacian operator or Sobel operator to detect the edge in the neighborhood window and increase the contrast of all pixels in the neighborhood window. The main irrational part of the current edge detection algorithm is that the current edge detection operator may not perfectly distinguish edge pixels from nonedge pixels. In order to overcome these shortcomings, we propose a new image enhancement method.

4. Image Contrast Enhancement Algorithm Based on Gray Prediction Model

In traditional image contrast enhancement algorithms, enhancing the local contrast is achieved by a convex function. This function can be constructed by a polynomial function or a power function. Here, power function is the most commonly used one. Many people design the exponential part of power function as a fixed fraction which is greater than zero and less than one. We have improved this index section before[15]: The exponential part of this power function can be changed by the gray entropy model and texture analysis, and the gray entropy of the four main directions of image neighborhood can be changed by following the change of image local texture. The difference between the maximum and minimum gray entropy values is used to measure the degree of image local edge. This approach has no problem with enhancing the main edge of image, but it is still not comprehensive enough to enhance some of the special edge parts. Here, we say that the gray prediction model has a high demand for modeling data conditions, that is, the data that do not meet the requirements of the model will lead to a poor accuracy. In the case of image data, if there is an edge in the image neighborhood, the data will be mutated, and the accuracy of the model will be worse. If it is a smooth area, the accuracy of the model can be controlled within a certain range that is acceptable. Because the gray prediction model is sensitive to capture the edge information, we can apply the gray prediction model to measure the degree of edge and adaptively enhance the current regional contrast, making the image edge more obvious and the nonedge part more smooth or at least not roughened.

4.1. *The idea of the algorithm*

If there is an edge across the current region of image, there must be a certain degree of grayscale mutation between the pixel gray values of image neighborhood. Regardless what the direction of this edge is, this mutation will lead to a certain degree of smoothness in local region of the image. At this time, with the image neighborhood pixel for gray modeling, the accuracy of the model is not as high as the smooth area. In a sense, the greater the degree of grayscale mutation is, the worse the smoothing of the current region of image will be, and the lower the accuracy of gray prediction modeling will be. Here, we need to increase the intensity of contrast more greatly, so as to make the contrast of edge more obvious, while making the smooth area softer and not dazzling. Therefore, it is possible to automatically control the degree of contrast enhancement in the current region of image through the gray prediction model for the image neighborhood pixel, so that the gray level change information of image data can be automatically passed to the contrast enhancement operation through the gray prediction model, thus improving the visual effect of the image and the convenience of the latter operation.

4.2. *The steps of the algorithm*

The whole operation is divided into two stages.

The first stage is the generated average residual value of the gray prediction model.

Suppose the image has a size of M rows and N columns. The current pixel is represented as $f(i,j)$, $(i = 2, 3, \ldots, M-1, j = 2, 3, \ldots, N-1)$.

In Step 1, in the 3×3 image neighborhood window, select all the pixels of the current neighborhood as the original sequence, that is,

$$\begin{aligned} X^{(0)} &= (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), x^{(0)}(5), x^{(0)}(6), x^{(0)}(7), x^{(0)}(8), x^{(0)}(9)) \\ &= \{f(i-1,j-1), f(i-1,j), f(i-1,j+1), f(i,j-1), f(i,j), f(i,j+1), \\ &\quad f(i+1,j-1), f(i+1,j), f(i+1,j+1)\}. \end{aligned} \tag{15}$$

In Step 2, since the data of the image neighborhoods are not far apart, there is a certain correlation among each other, and there is no temporal order among the data in the same region of image. The sorting data sequence is performed to improve the accuracy of the gray model, i.e.

$$\begin{aligned}X_s^{(0)} &= \mathrm{sort}(x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), x^{(0)}(4), x^{(0)}(5), x^{(0)}(6), x^{(0)}(7), x^{(0)}(8), x^{(0)}(9)) \\ &= (x_s^{(0)}(1), x_s^{(0)}(2), x_s^{(0)}(3), x_s^{(0)}(4), x_s^{(0)}(5), x_s^{(0)}(6), x_s^{(0)}(7), x_s^{(0)}(8), x_s^{(0)}(9)),\end{aligned} \tag{16}$$

where $x_s^{(0)}(1), x_s^{(0)}(2), \ldots, x_s^{(0)}(8), x_s^{(0)}(9)$ is organized in the ascending order of the sequence $x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(8), x^{(0)}(9)$, i.e.

$$\begin{aligned}&x_s^{(0)}(1) \le x_s^{(0)}(2) \le x_s^{(0)}(3) \le x_s^{(0)}(4) \le x_s^{(0)}(5) \le x_s^{(0)}(6) \le x_s^{(0)}(7) \le x_s^{(0)}(8) \\ &\qquad \le x_s^{(0)}(9).\end{aligned}$$

In Step 3, the above data is made by once accumulating generation operator, that is,

$$\begin{aligned}X_s^{(1)} &= (x_s^{(1)}(1), x_s^{(1)}(2), x_s^{(1)}(3), x_s^{(1)}(4), x_s^{(1)}(5), x_s^{(1)}(6), x_s^{(1)}(7), x_s^{(1)}(8), x_s^{(1)}(9)) \\ &= \Bigg(x_s^{(0)}(1), \sum_{l=1}^{2} x_s^{(0)}(l), \sum_{l=1}^{3} x_s^{(0)}(l), \sum_{l=1}^{4} x_s^{(0)}(l), \sum_{l=1}^{5} x_s^{(0)}(l), \sum_{l=1}^{6} x_s^{(0)}(l), \\ &\quad \sum_{l=1}^{7} x_s^{(0)}(l), \sum_{l=1}^{8} x_s^{(0)}(l), \sum_{l=1}^{9} x_s^{(0)}(l)\Bigg).\end{aligned} \tag{17}$$

In Step 4, make the above once accumulating generation sequence to mean sequence generated by consecutive neighbors.

$$\begin{aligned}Z_s^{(1)} &= (z_s^{(1)}(1), z_s^{(1)}(2), \ldots, z_s^{(1)}(8)) \\ &= (0.5 \cdot (x_s^{(1)}(1) + x_s^{(1)}(2)), 0.5 \cdot (x_s^{(1)}(2) + x_s^{(1)}(3)), \ldots, 0.5 \cdot (x_s^{(1)}(7) + x_s^{(1)}(8)), \\ &\quad 0.5 \cdot (x_s^{(1)}(8) + x_s^{(1)}(9)))\end{aligned} \tag{18}$$

In Step 5, calculate the parameter sequence of the GM(1,1) model: If it is set that

$$Y = \begin{bmatrix} x_s^{(0)}(2) \\ x_s^{(0)}(3) \\ \vdots \\ x_s^{(0)}(9) \end{bmatrix}, \quad B = \begin{bmatrix} -z_s^{(1)}(2) & 1 \\ -z_s^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z_s^{(1)}(9) & 1 \end{bmatrix},$$

then

$$P = (B^T B)^{-1} B^T Y = \begin{bmatrix} a \\ b \end{bmatrix}. \tag{19}$$

In Step 6, the time response sequence of the gray differential equation GM(1,1) is

$$\hat{x}_s^{(1)}(k+1) = \left(x_s^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, \quad k = 1, 2, \ldots, 8. \tag{20}$$

Inversely accumulate to restore the fitted sequence:

$$\hat{x}_s^{(0)}(k+1) = \hat{x}_s^{(1)}(k+1) - \hat{x}_s^{(1)}(k) = (1 - e^{a})\left(x_s^{(0)}(1) - \frac{b}{a}\right)e^{-ak}, \quad k = 1, 2, \ldots, 8. \tag{21}$$

Then, the restored sequence is

$$\hat{X}_s^{(0)} = (\hat{x}_s^{(0)}(1), \hat{x}_s^{(0)}(2), \hat{x}_s^{(0)}(3), \hat{x}_s^{(0)}(4), \hat{x}_s^{(0)}(5), \hat{x}_s^{(0)}(6), \hat{x}_s^{(0)}(7), \hat{x}_s^{(0)}(8), \hat{x}_s^{(0)}(9)),$$

where $\hat{x}_s^{(0)}(1) = x_s^{(0)}(1)$, others can be obtained by Eq. (21).

In Step 7, calculate the average residual of the GM(1,1) model at the location (i, j)

$$E(i,j) = e^{(0)}(i,j) = \frac{1}{9}\sum_{l=1}^{9}|e^{(0)}(l)| = \frac{1}{9}\sum_{l=1}^{9}|x_s^{(0)}(l) - \hat{x}_s^{(0)}(l)|. \tag{22}$$

So, we can get the average residual of the image at each point, so as to determine to what degree the current point is in the edge of a local region. The larger the average residual is, the more likely it is that the current point is in the edge region, and vice versa, the current point is more likely to be in a smooth area.

The second stage is mainly that the image contrast is enhanced by the average residual value of the GM(1, 1).

In Step 8, calculate the average value of the image neighborhood window (not including the center point), and construct the contrast of current point.

$$v(i,j) = \frac{1}{8}\left[\left(\sum_{h=i-1}^{i+1}\sum_{l=j-1}^{j+1} f(h,l)\right) - f(i,j)\right], \tag{23}$$

$$c(i,j) = \frac{|f(i,j) - v(i,j)|}{|f(i,j) + v(i,j)|}. \tag{24}$$

Obviously, the range of the contrast is [0, 1].

In Step 9, with the average residual error taken as the exponential part, θ is a pending unknown parameter for the bottom part, and $\theta > 1$, all constructed as an exponential part of the contrast enhancement operator, so the contrast enhancement operator is obtained.

$$C'(i,j) = c(i,j)^{\theta^{-E(i,j)}}. \tag{25}$$

In the above operator, when the edge at the location (i, j) appears, the average residual $E(i, j)$ of GM(1,1) becomes larger, $\theta^{-E(i,j)}$ smaller (which is between 0 and 1), and $C'(i, j)$ larger, which increase the contrast of edge area; on the contrary, when the point $f(i,j)$ is in the smooth region, and the current region has no edges or very weak edges, then the average residuals $E(i,j)$ of GM(1,1) will become smaller, $\theta^{-E(i,j)}$ larger (still between 0 and 1), and $C'(i,j)$ smaller. The contrast of the smooth area is appropriately suppressed to avoid excessive increase. The traditional contrast enhancement operator is usually achieved by a power function (e.g. $C' = c^{0.5}(0 \leq c \leq 1)$) with a fixed exponent. Since the exponential part of the power function is a fixed constant, at this time, whether it is smooth area or edge area, the operator enhances the contrast at a relatively fixed scale, which is not conducive to the appropriate expansion of the contrast between nonedge region and edge region. In this case, the contrast of nonedge area is also greatly enhanced with the increased contrast of edge area, which is one of the problems that we need to overcome in image contrast enhancement.

In Step 10, according to the contrast formula (24), the new central pixel value of current neighborhood window after enhanced processing is solved;

$$\hat{f}(i,j) = \begin{cases} \dfrac{1 + C'(i,j)}{1 - C'(i,j)} \cdot v(i,j), & f(i,j) > v(i,j), \\ \dfrac{1 - C'(i,j)}{1 + C'(i,j)} \cdot v(i,j), & f(i,j) \leq v(i,j). \end{cases} \tag{26}$$

So that we get a new pixel value of the enhanced current position in the image neighborhood window. When the neighborhood window traverses the entire image area from top to bottom and from left to right on the image, the entire image completes the contrast enhancement operation.

The framework and flow chart of the algorithm are given in Fig. 1.

4.3. *Algorithm results and its analysis*

As the image contrast is enhanced, it lays a foundation for the subsequent image edge detection. Good contrast enhancement quality can further improve the quality of image edge detection, while the image edge detection quality would reflect the level of the image contrast enhancement effect from the other side. Therefore, this paper gives the results of image contrast enhancement and its corresponding edge detection, and through the edge detection results, it takes another perspective to evaluate whether the corresponding image enhancement effect is good or bad. Using MATLAB software programming experiment, compared with the results of traditional image contrast enhancement[1] and its corresponding edge detection, fuzzy contrast enhancement[16] and its corresponding edge detection, adaptive image enhancement algorithm based on fuzzy contrast of gray entropy[17] and its corresponding edge detection, we select several different parameters θ to adjust the enhanced strength in our improved algorithm. The results are shown in Figs. 2 and 3.

From the results of the experimental images, the contrast of original image is not high, resulting in a poor quality of edge detection and not very obvious main edge.

Since the traditional contrast enhancement algorithm improves the image quality, the overall image contrast has also been improved. The corresponding edge detection results are better than those without contrast enhancement processing, but the edge area is still not very obvious. The algorithm in Ref. 16 has a good effect on fine edge

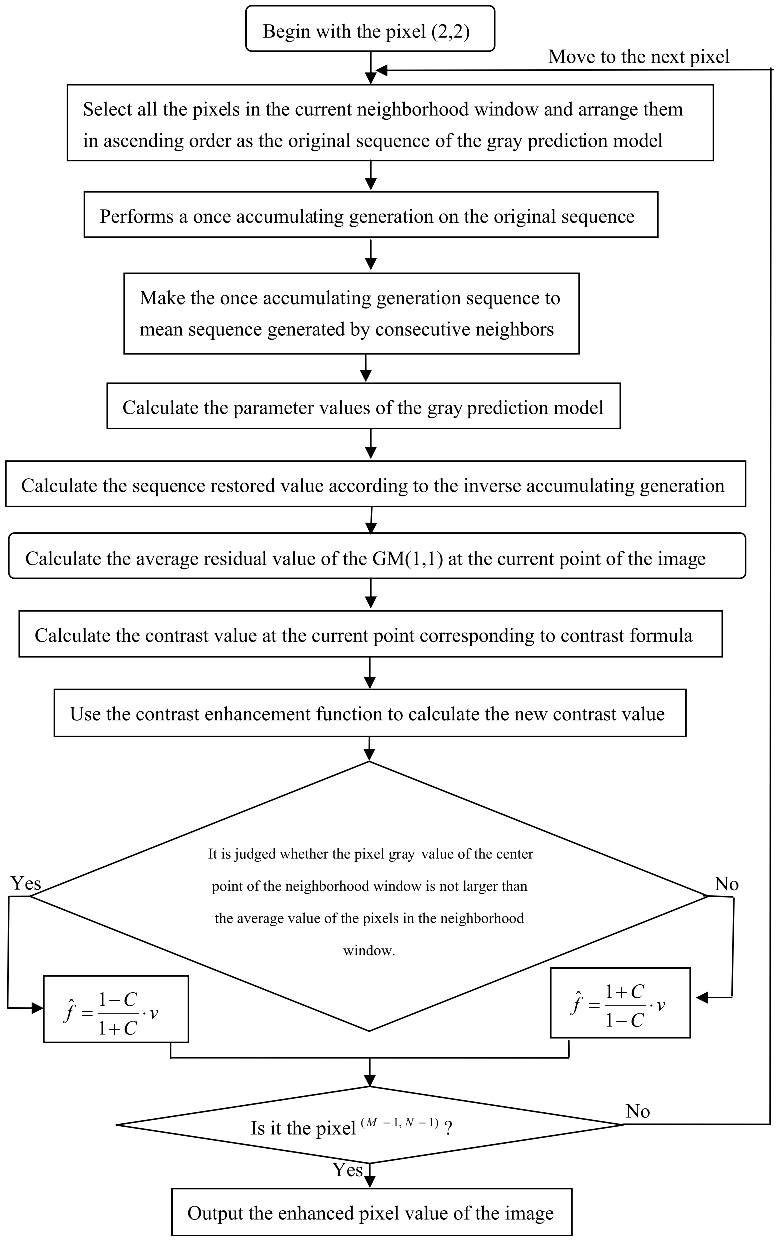


Fig. 1. Algorithm flow chart.

areas such as girls' hairs, but at the same time, it makes the smooth areas of image rough. In Ref. 17, the gray entropy is introduced into fuzzy contrast enhancement algorithm, which improves the effect of algorithm execution to a certain extent. In this paper, a total of four different parameter values are selected for the proposed new

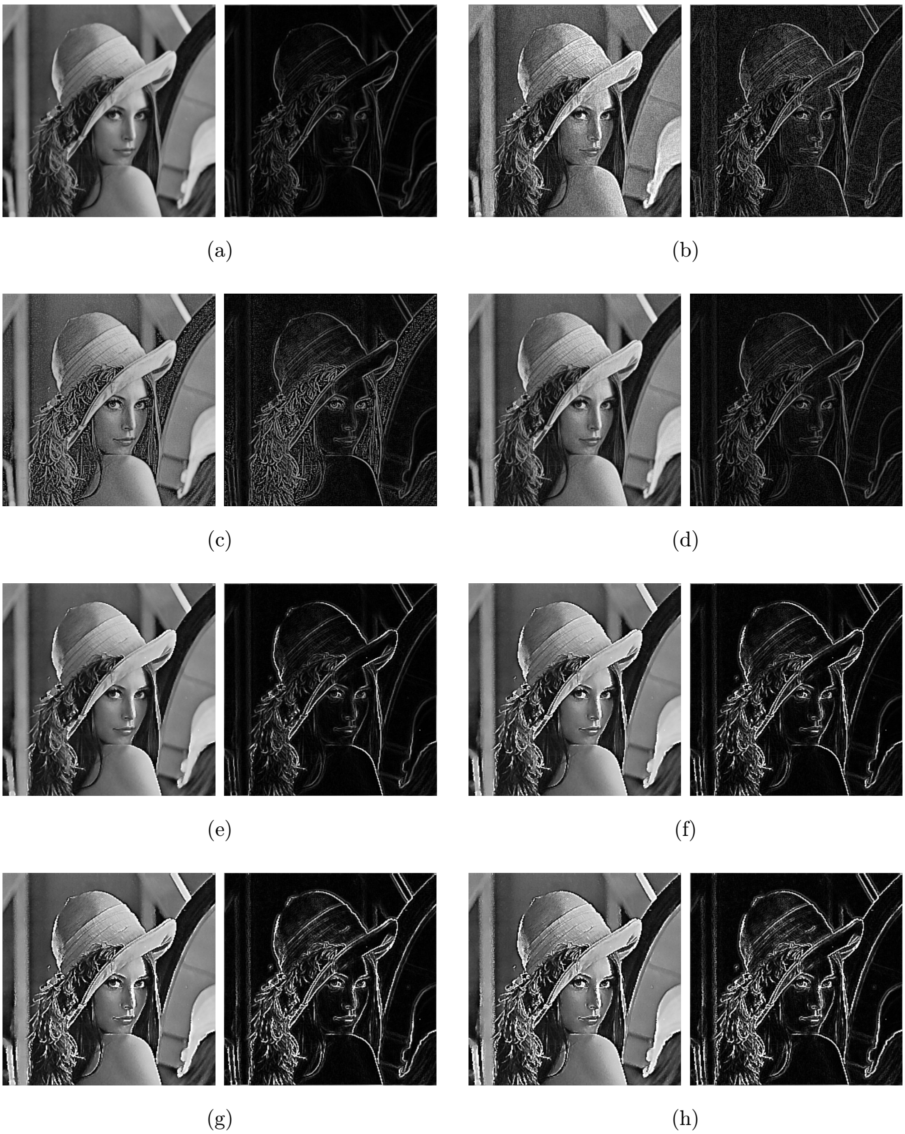
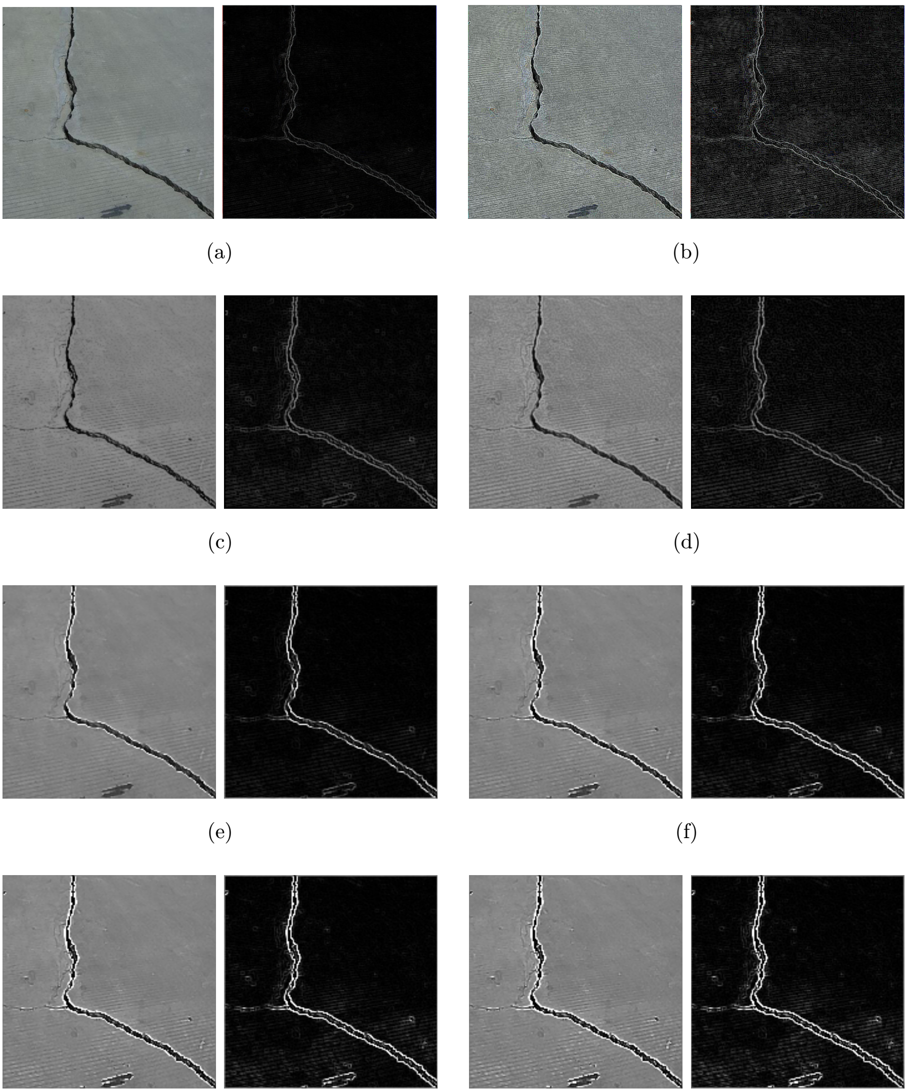


Fig. 2. Experimental image and its edge detection results. (a) Original image and its edge detection, (b) Traditional contrast enhancement[1] and edge detection, (c) Fuzzy contrast enhancement[16] and edge detection, (d) Contrast enhancement[17] and edge detection, (e) New algorithm and its edge detection ($\theta = 1.1$), (f) New algorithm and its edge detection ($\theta = 1.2$), (g) New algorithm and its edge detection ($\theta = 1.3$) and (h) New algorithm and its edge detection ($\theta = 1.4$).

algorithm. The contrast enhancement effect of the image is more clear with the increased threshold, and the contrast of edge area of the girl's subtle hair, hat, eyes, nose, lips and other main contours is amplified, but the pixel grayscale fluctuations of some nonedge areas are well suppressed.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 3. Pavement image and its edge detection results. (a) Original image and its edge detection, (b) Traditional contrast enhancement[1] and edge detection, (c) Fuzzy contrast enhancement[16] and edge detection, (d) Contrast enhancement[17] and edge detection, (e) New algorithm and its edge detection ($\theta = 1.1$), (f) New algorithm and its edge detection ($\theta = 1.2$), (g) New algorithm and its edge detection ($\theta = 1.3$) and (h) New algorithm and its edge detection ($\theta = 1.4$).

From the experimental results of the pavement image, the crack edge of the original unenhanced image can hardly be seen. The traditional contrast enhancement algorithm makes the crack edge of image enhanced to a certain degree, but it is still looming. The methods in Refs. 16 and 17 have made great progress in detecting cracks in pavement image, and the crack area becomes relatively obvious, but there is still much room for improvement which needs us to work hard. The contrast enhancement algorithm proposed in this paper is a good way to achieve obvious enhancement on edge of the crack. The edge of the crack is dazzling, but the nonedge area of image is still in a smooth state, which achieves the desired effect. At the same time, according to the human visual experience and following-up further processing needs, we can select appropriate parameter values to get an appropriate degree of enhancement effect.

5. Conclusion

This paper starts from the difficulty of gray prediction model applied into image enhancement processing, and realizes that gray prediction model has a high demand for modeling data smoothness. The gray prediction model has the characteristics of sensitivity to the edge region of pixel, and the average residual value of gray prediction model is used to measure the degree of the nonsmoothness of current area, and dynamically adjusts the enhancement scale of image local contrast. Compared with other traditional contrast enhancement operators, in the proposed algorithm, the exponential part of the contrast enhancement operator can absorb the fluctuation amplitude of the local image texture in time, and increase the contrast of the edge region to a larger extent, while the scale of the contrast enhancement of the nonedge region is moderately controlled. The edge region and nonedge region of the image are treated in different ways on the scale of contrast enhancement, so as to achieve the effect of improving the quality of image processing. From the corresponding edge detection effect, the algorithm in this paper meets the requirement of image contrast enhancement, and it is an effective image contrast enhancement method. But, there are still some issues that need to be discussed later. The first is about the optimization of parameters in the contrast enhancement process. The current use of computer search is the way to select the parameter value, which needs to spend a lot of computer running time, and also needs to combine the subjective recognition of human eyes. These have increased the uncontrollability of the algorithmic program. The second is that the parameters chosen in this paper also have the problem of oversized grayscale, which indicates that the degree of contrast enhancement is too high. These problems cause the contrast of some edge regions in image within a normal range. At the same time, the setting of the original sequence of gray prediction model and the influence of the gray prediction model-type on the accuracy of the model proposed in this paper need to be further explored. Later, we will discuss these problems to improve the quality and efficiency of image processing.

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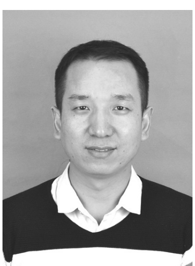

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