

# DIP Assignment 1

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## Abstract

Intensity transformation is the simplest technology in digital image processing. It is often used in the field of image enhancement. In this way, functions are used to map the intensity of the original pixel to the target intensity. And interpolation is a basic method widely adopted in tasks such as enlargement, contraction, rotation, and geometric correction. Fundamentally, interpolation is the process of using known data to estimate the intensity of an unknown location. These methods are often used in digital image processing.

## 1 Introduction and Overview

Li Hua is a pulmonologist at Tongji Hospital and has been fighting the COVID-19. Since CT is one of the most common detection methods for COVID-19, Li Hua and his department have to check a huge number of CT images every day. However, Li Hua has run into some troubles recently. To help Li Hua, two widely used image processing methods will be used, namely intensity transformation and interpolation. The former enhances the image effect, while the latter enlarges the images. This will greatly help image recognition and disease diagnosis.

## 2 Problem 1: CT contrast enhancement

In this part, the main method is the intensity transformation. Through the intensity transformation, the unrecognizable image can become bright and clear. In this section, the main method used is histogram equalization and the contrast limited adaptive histogram equalization. Finally,  $\gamma$ -nonlinear mapping will be taken into implement to restore the current darkened image to the original. These are the various methods used in this section.

### 2.1 Intensity Histogram

#### 2.1.1 Intensity Histogram

The histogram is the basis of a variety of spatial domain processing techniques. The intensity histogram is a function of the intensity distribution, which is the statistics of the distribution in the image. The intensity histogram is to count all the pixels in the digital image according to the size of the intensity value and count the frequency of their appearance. The histogram is a function of intensity that represents the number of pixels with a certain value in the image and reflects the frequency of it in the image. In this section, the histogram is used to calculate the number of integer occurrences in the interval  $[0, 255]$ . The histogram is formed by the number of different intensity that appears in the pixel. Through this histogram, we can easily see the distribution of the value, so that we can more intuitively judge the overall light and dark degree of the picture.

#### 2.1.2 Image Analysis

In this section, a picture will be extracted from the dataset for corresponding analysis and discussion. The example selected from the dataset is CT\_3, while various histograms in the data set are made. In the process

of making the histogram, it should be considered that the characteristics of the computer storage start at 0, so when displaying in the histogram, the intensity should be increased by one. The picture of CT\_3 and its histogram is shown as follows.

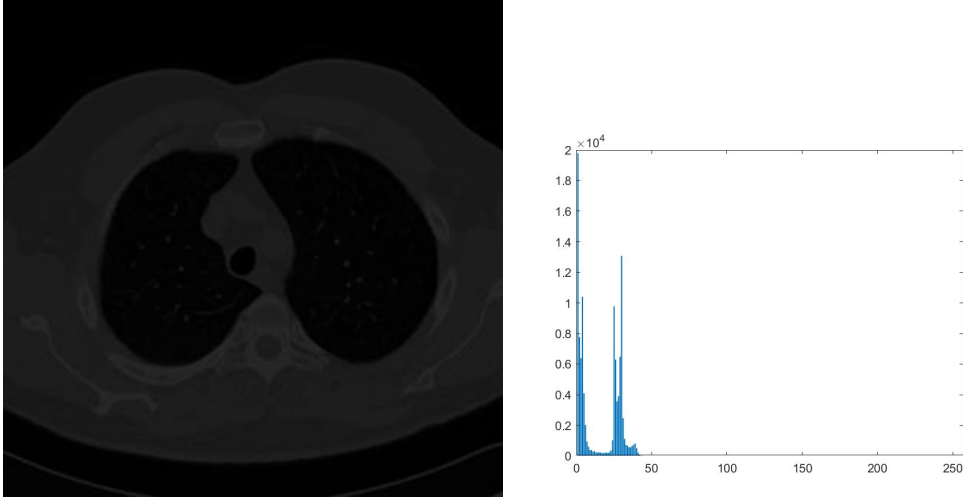


Figure 1: This is the CT\_3

It can be seen from CT\_3 that the overall color of this picture is dark because of the weak intensity. It can be estimated that most of the intensity of this picture is concentrated in the first half of the histogram, which means most of the intensity is distributed in places with small values. The quality of the whole picture is terrible, and the effect is too poor to identify the location of the lesion.

It can be seen from the histogram that the pre-specified distribution of the intensity of the original image is roughly correct. It can be seen that in the histogram, the part with weaker intensity occupies most of the pixels, while the part with stronger intensity does not exist in the pixels. Therefore, a black picture appears so that it is not easy to obtain ideal medical images that are helpful for diagnosis.

## 2.2 Histogram Equation

### 2.2.1 Histogram Equation

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark.

We use the following formula to calculate the intensities distribution after the histogram equalization.

$$s_k = T(r_k) = (L-1) \sum_{j=0}^k p_r(r_j) = \frac{(L-1)}{MN} \sum_{j=0}^k n_j, \quad k = 0, 1, 2, \dots, L-1 \quad (1)$$

Where  $MN$  represents the number of the pixels,  $s_k$  the transformed intensity,  $n_k$  the number of the  $r_k$  pixels.

### 2.2.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_3. The image of CT\_3 and the transformed image is shown as follows.

Through the comparison of the two images, the original image is darker while the new image is brighter on the original basis. Compared with the original, the new image can see more details. However, it also has

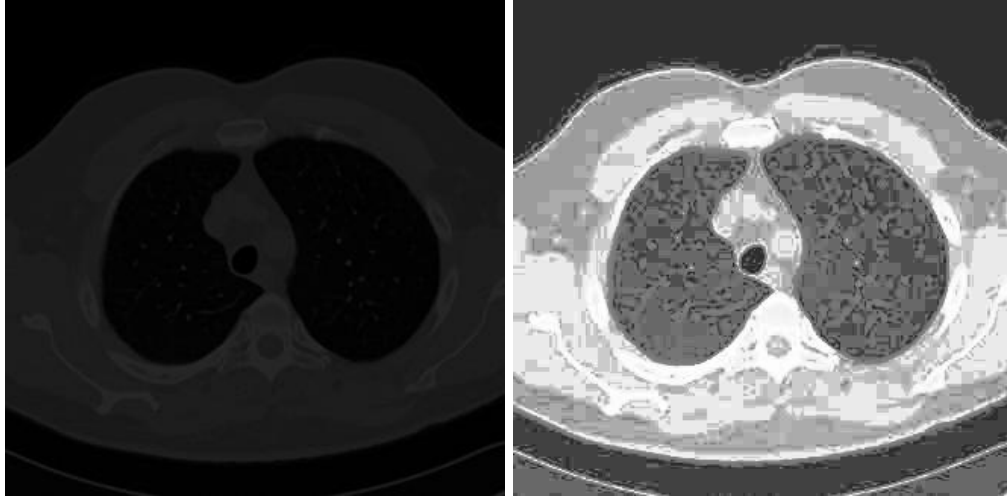


Figure 2: This is the contrast between CT\_3 and the transformed image

some corresponding problems. It has some rectangular patches in some positions with the details blurred, which has a great influence on the effect.

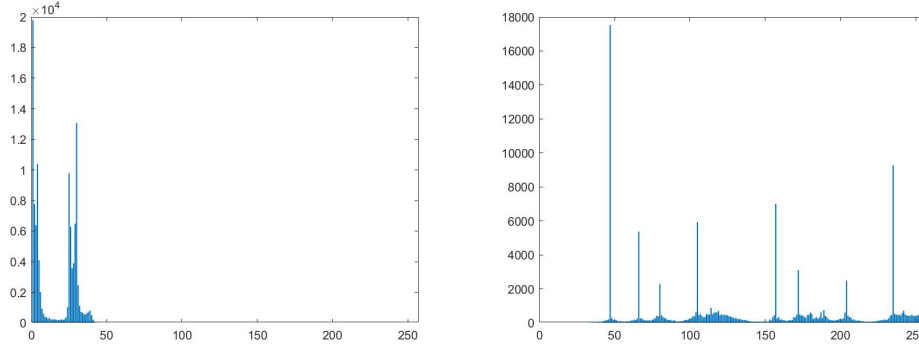


Figure 3: This is the contrast between the histograms

Through the comparison of the two histograms, we found that the pixels of the original histogram are distributed in the positions with weaker intensities, while the new histogram is distributed in all interval positions. Therefore, the original image is dark, while the new image is relatively brighter.

In general, the effect of histogram equalization is good. Some flaws cannot be dealt with. For example, the blurring of the picture caused by histogram equalization is not satisfactory.

## 2.3 Contrast Limited AHE

### 2.3.1 Contrast Limited AHE

Adaptive histogram equalization differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. Contrast Limited AHE is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification.

In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the neighbourhood cumulative distribution function and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF

and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region.

### 2.3.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_1. The image of CT\_3 and the transformed image is shown as follows.

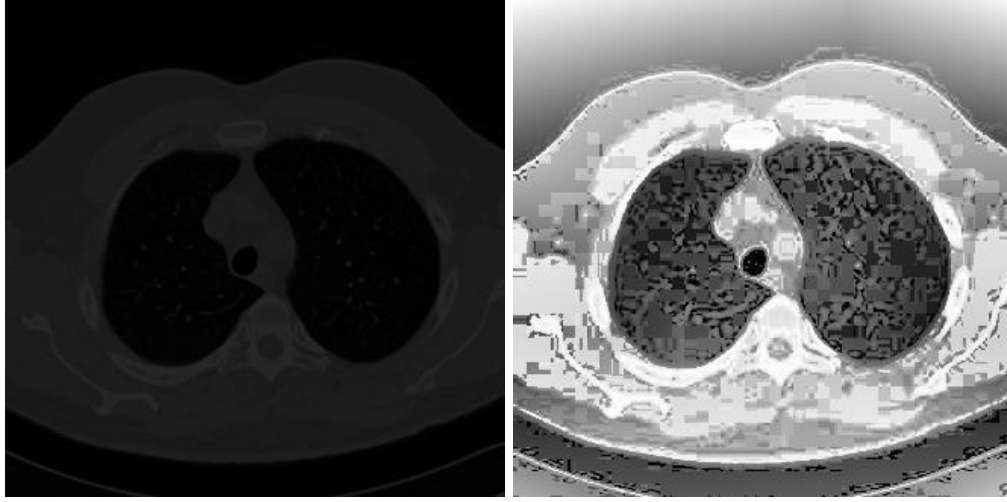


Figure 4: This is the contrast between CT\_3 and the transformed image

By comparing the transformed image with the original and the histogram equalization one, it can be found that the CLAHE method improves the contrast of the image after intensity transformation more. In the experiment, the parameters of CLAHE are set to 16 tiles, and the clipping limit is set to 0.56. This makes the image not lose much information and be distorted, and greatly improves the contrast which makes the image brighter.

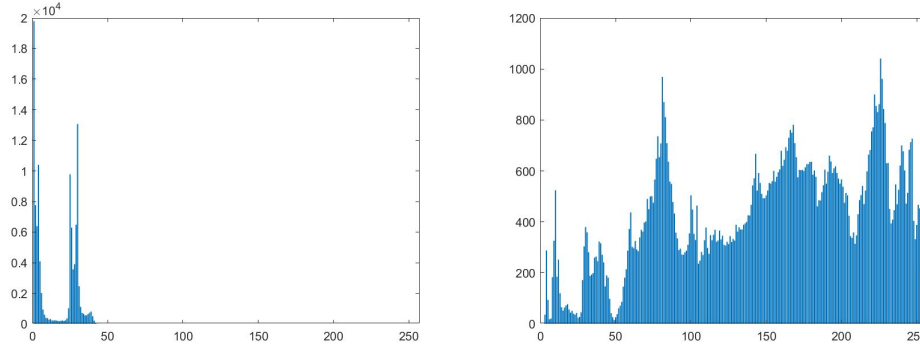


Figure 5: This is the contrast between the histograms

Through the comparison of the two histograms, we find that the pixels of the original histogram is distributed in the positions with weaker intensity, while the new histogram after CLAHE is distributed in all interval positions. But we can see that the number of histograms at a certain point in the middle is also very large. This is because, after the slice equalization, the middle intensity accumulates the most.

## 2.4 Power Law transformations

### 2.4.1 Power Law transformations

Power law transformations have the following form

$$s = cr^\gamma \quad (2)$$

where  $c$  and  $\gamma$  are positive constants.

Power-law curves with fractional values of  $\gamma$  map a narrow range of dark input values to a wider range of output values, with the opposite being true for higher values of input levels. Varying  $\gamma$  gives a whole family of curves.

When the intensities of the input image undergo power law transformation, they are often normalized. It has the following formula

$$s = \left( \frac{r - lIN}{hIN - lIN} \right)^\gamma \cdot (hOUT - lOUT) + lOUT \quad (3)$$

### 2.4.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_3 too. The image of CT\_3 and the image after power law transformation is shown as follows.

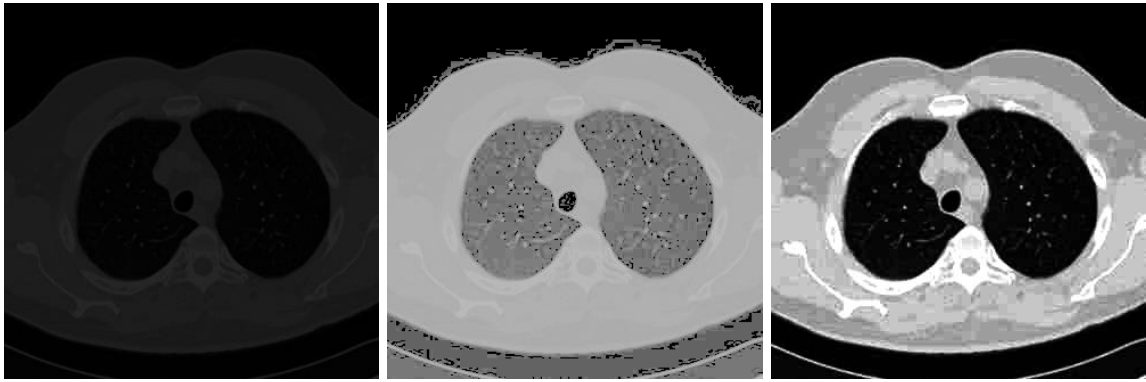


Figure 6: This is the contrast between CT\_3 and the transformed image

In power law transformation we use a gamma value of 0.2. It can be seen that the effect is not very satisfactory. This is the image processed after normalization. When the obtained gamma value is less than 1. Its function is to amplify the gray values in the dark area. You can see that the brightness of the picture has become brighter, but there is no good effect. Infer the original image requires direct power operation.

In the new power law transformation, we use a larger power law value. Compared with the normalized transformation, the gamma value we currently obtain is less than 1. So its function is to amplify the intensity in the dark area. We can see many details in the transformed image. Compared with the previous two methods, this transforms the picture back to its original state.

## 3 Problem 2: Resizing X-ray images

In computer image processing and computer graphics, image scaling refers to the process of adjusting the size of digital images. Image scaling is a non-trivial process that requires a trade-off between processing efficiency and the smoothness and sharpness of the result. When the size of an image increases, the visibility of the pixels that make up the image will become higher, making the image appear "soft". Conversely, shrinking an image will enhance its smoothness and clarity.

## 3.1 Nearest-neighbor Interpolation

### 3.1.1 Nearest-neighbor Interpolation

Nearest-neighbor interpolation is a simple method of multivariate interpolation in one or more dimensions. Interpolation is the problem of approximating the value of a function for a non-given point in some space when given the value of that function in points around (neighboring) that point. The nearest neighbor algorithm selects the value of the nearest point and does not consider the values of neighboring points at all, yielding a piecewise-constant interpolant.

### 3.1.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_1. The image of CT\_1 and the resized is shown as follows.

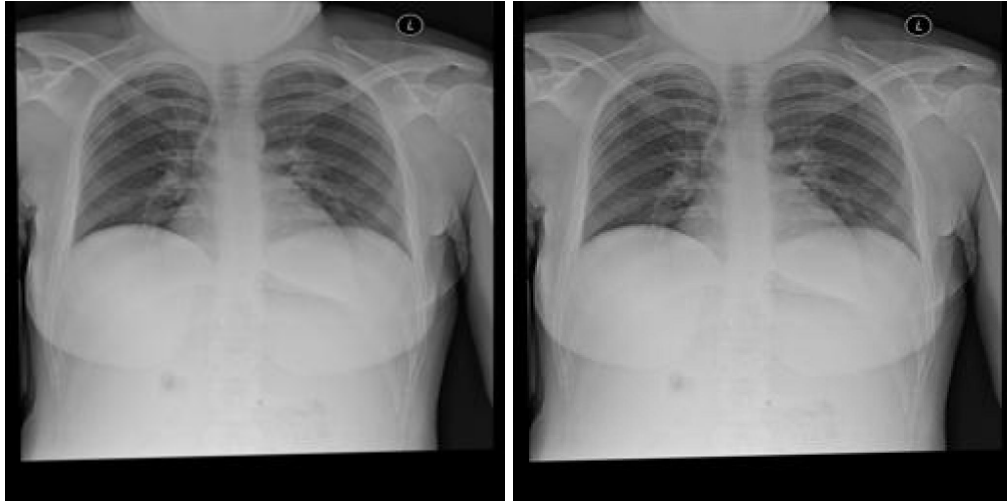


Figure 7: This is the contrast between CT\_1 and the resized image

In the enlarged image, we can clearly see the jaggedness, which is determined by the nature of the nearest neighbor interpolation method. It fills adjacent pixels to the vacant position. Therefore, jagged pixels appear at the edge of the image, which is the limitation of this method. Although the original picture is successfully enlarged, the original picture is sharpened, which may cause a serious decline in picture effect and lack of information. Therefore, it is rarely used.

Nearest neighbor interpolation is to take the intensity of the nearest neighbor among the four neighboring pixels around the sampling point. The nearest neighbor interpolation algorithm is the fastest, but it will produce obvious aliasing and mosaic phenomena.

## 3.2 Bilinear interpolation

### 3.2.1 Bilinear interpolation

In mathematics, bilinear interpolation is an extension of linear interpolation for interpolating functions of two variables on a rectilinear 2D grid. Bilinear interpolation is performed using linear interpolation first in one direction, and then again in the other direction. Although each step is linear in the sampled values and in the position, the interpolation as a whole is not linear but rather quadratic in the sample location. Bilinear interpolation is one of the basic resampling techniques in computer vision and image processing, where it is also called bilinear filtering or bilinear texture mapping.

Bilinear interpolation has the following formula.

$$\begin{aligned}
f(x, y) &\approx \frac{y_2 - y}{y_2 - y_1} f(x, y_1) + \frac{y - y_1}{y_2 - y_1} f(x, y_2) \\
&= \frac{y_2 - y}{y_2 - y_1} \left( \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21}) \right) + \frac{y - y_1}{y_2 - y_1} \left( \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22}) \right) \quad (4) \\
&= \frac{1}{(x_2 - x_1)(y_2 - y_1)} \begin{bmatrix} x_2 - x & x - x_1 \end{bmatrix} \begin{bmatrix} f(Q_{11}) & f(Q_{12}) \\ f(Q_{21}) & f(Q_{22}) \end{bmatrix} \begin{bmatrix} y_2 - y \\ y - y_1 \end{bmatrix}
\end{aligned}$$

### 3.2.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_1 too. The image of CT\_1 and the resized is shown as follows.

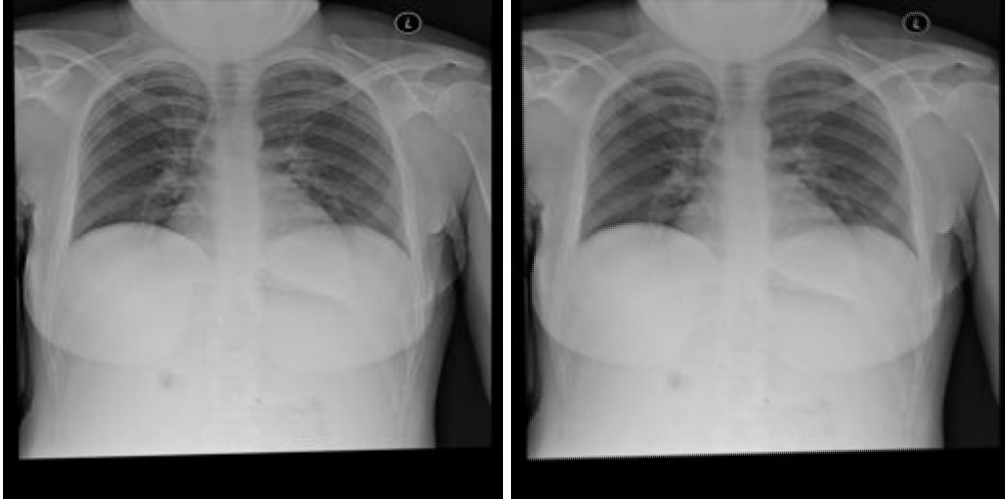


Figure 8: This is the contrast between CT\_1 and the resized image

In the enlarged image with this algorithm, we can also clearly see the pixels of small squares, which is determined by the nature of bilinear interpolation. It will use four adjacent pixels to fill the gap through a linear interpolation algorithm. Therefore, the image will present a kind of out of place fuzzy feeling. But compared with the nearest neighbor interpolation method, it has been greatly improved.

Bilinear interpolation uses the intensities of the surrounding four neighboring points to do linear interpolation in two directions to obtain the values of the sampling points. This method eliminates the aliasing to a large extent, but it becomes blurry on the edges.

## 3.3 Bicubic interpolation

### 3.3.1 Bicubic interpolation

In mathematics, bicubic interpolation is an extension of cubic interpolation for interpolating data points on a two-dimensional regular grid. The interpolated surface is smoother than corresponding surfaces obtained by bilinear interpolation or nearest-neighbor interpolation. Bicubic interpolation can be accomplished using either Lagrange polynomials, cubic splines, or cubic convolution algorithm.

In image processing, bicubic interpolation is often chosen over bilinear or nearest-neighbor interpolation in image resampling, when speed is not an issue. In contrast to bilinear interpolation, which only takes 4 pixels into account, bicubic interpolation considers 16 pixels. Images resampled with bicubic interpolation are smoother and have fewer interpolation artifacts.

Bicubic spline interpolation requires the solution of the linear system described above for each grid cell. An interpolator with similar properties can be obtained by applying a convolution with the following kernel in both dimensions:

$$W(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1 & \text{for } |x| \leq 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a & \text{for } 1 < |x| < 2 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where  $a$  is usually set to  $-0.5$  or  $-0.75$ . Note that  $W(0) = 1$  and  $W(n) = 0$  for all nonzero integers  $n$ .

### 3.3.2 Image Analysis

In this section, the extracted image from the dataset for corresponding analysis and discussion is CT\_1 too. The image of CT\_1 and the resized is shown as follows.



Figure 9: This is the contrast between CT\_1 and the resized image

In the image enlarged using this algorithm, a more perfect enlarged image is obtained. The algorithm uses 16 neighboring pixels as parameters to fill in the current vacant values and uses matrix operations to process the parameters one by one. Looking at the image, it is found that the original image effect is perfectly enlarged by the algorithm, but it is slightly blurred.

Bicubic interpolation not only considers the intensities of the four neighboring points but also considers the influence of the intensity change rate between each neighboring point. It is an improved algorithm of bilinear interpolation. Compared with the first two classical interpolation methods, better interpolation results can be achieved. But it still has low-pass filtering, which will lose the high-frequency part of the interpolated image, so the image edge is blurred.

## 4 Conclusion

In this report, the basic intensity transformation method is used for image enhancement and interpolation to enlarge the picture. Intensity transformation is the simplest technology in digital image processing which is often used in the field of image enhancement. The interpolation is a basic method widely adopted in enlargement. Both of them are the effective ways to process the image to meet demands in other fields.