Surface Reconstruction Method of Color 3D Image Based on Independent Adjustable Sparse Coefficient

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Abstract. Color 3D images play an important role in many fields. The segmentation effect of traditional 3D image surface reconstruction methods is poor, resulting in unreliable reconstruction results. Therefore, a new surface reconstruction method of color 3D image is designed based on the independent adjustable sparse coefficient. Firstly, the color 3D image is enhanced, and then the point cloud registration algorithm is designed based on the independent adjustable sparse coefficient. The surface reconstruction of the color 3D image is realized by the point cloud registration algorithm. The experimental results show that the reconstruction effect of this method is good, which proves that it has high application value.

Keywords: Independently adjustable sparsity coefficient · Color three-dimensional image · Surface reconstruction · Image enhancement · Point cloud registration algorithm

1 Introduction

Vision is the main way for human beings to capture information from the real world. However, the information obtained from two-dimensional scene is limited. Therefore, three-dimensional technology has emerged [1]. Computer vision is to make the computer have the ability to perceive and analyze the information of the external environment, install "eyes" for the computer, and make it have the function similar to human eyes. This technology enables the machine to record the physical information of the object in the environment, and then analyze and calculate the object [2].

Relevant scholars summarized the research results of many disciplines in 1982 and put forward a series of computer vision theories. Its core idea is to reconstruct the three-dimensional structure through two-dimensional images. Computer vision has attracted more and more attention and has been applied to various fields, such as visual image processing, various inspection and monitoring, robot autonomous recognition and instrument navigation, commercial field, space technology and military simulation [3].

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The research of 3D reconstruction technology involves many disciplines and is a hot research direction in the field of computer vision technology. It is to explore how to build the two-dimensional model of the object into a three-dimensional model in the computer, so that the computer can analyze and process it. In the process of reconstructing object model, depth image acquisition and model reconstruction are the most key parts. The depth image, also known as the distance image, can be obtained by a three-dimensional information sampling device. However, due to the limitations of the principle of the equipment itself, the obtained depth image will have problems such as black holes and noise, so it is necessary to enhance the depth image. The key step in model reconstruction is to convert the obtained 3D data point cloud data into the 3D surface model of the object, which is also called point cloud registration. The quality of reconstruction results will be directly affected by the accuracy of point cloud registration. Therefore, in order to obtain a 3D model with high reconstruction degree, it is necessary to realize high-precision point cloud registration [4].

With the development of computer hardware and software technology, the world presented by two-dimensional images can no longer satisfy people's visual experience, and thus the depth image is born, and then the three-dimensional real world is obtained. Nowadays, it has become easier to obtain better depth image information using depth sensors, making depth images the focus of researchers, and applications based on depth images are also developing rapidly [5].

In recent years, technological progress has promoted the development of reverse engineering research. In reverse engineering, you first need to use a laser scanner to obtain geometric data, and then obtain a three-dimensional model of the object through certain operations [6]. The update of laser measurement technology makes the laser scanner more efficient, lighter and more powerful, so that the acquired point cloud data is more accurate, providing a solid foundation for deeper application, and it has demonstrated powerful functions in all walks of life. The advancement of nature and technology.

Based on the above analysis, this paper designs a new surface reconstruction method of color 3D image based on independently adjustable sparse coefficients. In this study, the method firstly enhances the detail delicacy in color 3D image, and fundamentally improves the reconstruction effect by clarifying the detail information. Then, a point cloud registration algorithm was designed based on the independent adjustable sparse coefficients, and the surface reconstruction of color 3D images was realized through the point cloud registration algorithm.

2 Method Design

2.1 Color 3D Image Enhancement Processing

The pixel in the grayscale image represents the brightness value, and the pixel in the depth image represents the distance from the point to the camera, that is, the depth value or distance value, so the depth image is also called the distance image [7]. The relationship between depth image and grayscale image is shown in Fig. 1.

As can be seen from Fig. 1, the depth value represents the distance between the target point and the measuring instrument. Because the depth value is only related to

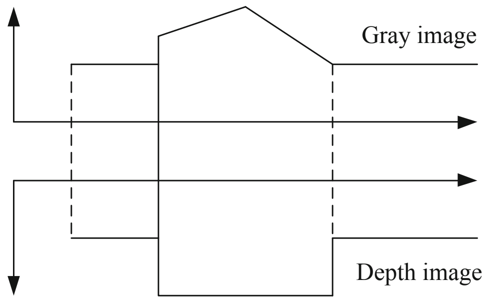

Fig. 1. The relationship between depth image and grayscale image

the distance and has nothing to do with external factors, the depth image can correctly reflect the physical depth information of the scene. By constructing the three-dimensional model of the object, it can provide a more solid foundation for higher-level computer vision applications.

The primary task in 3D reconstruction is to obtain the 3D information of the object, and the depth sensor has become an indispensable device to obtain the depth information of the object [8]. The depth sensor can be divided into active depth imaging sensor and passive depth imaging sensor according to the need for external emission light source. The active depth imaging sensor needs the help of external emission light source when collecting image information. The passive depth imaging sensor is just opposite to the active depth sensor. It only uses its own principle and the information existing in the environment when collecting image information, and does not need the help of external emission light source. The following is a brief overview of the technologies involved in the depth sensor.

Stereo vision technology is a passive depth imaging technology without external light source. Stereo vision technology reconstructs three-dimensional information of the scene by obtaining multiple images from different perspectives from multiple cameras at multiple locations. So far, stereo vision technology has a relatively perfect and mature system, which can be divided according to the number of images required in the process of three-dimensional reconstruction. If the number of images required is 2, two images taken from two different directions of the same scene are needed to obtain depth information. It is also called binocular stereo vision technology because of its similar structure to the information acquired by the human eye [9].

Lidar ranging technology requires the use of laser light sources to calculate depth information based on the time difference between laser emission and reception and the light propagation speed. Its core technology is light flight time ranging technology. When using laser ranging, the light source periodically emits a laser signal to the measured object, and then the signal hits the measured object and returns to the imaging device. Record the time required for this process, and then the distance between the camera and each surface of the object It can be calculated from this time. The advantages and disadvantages of these technologies are shown in Table 1.

Table 1. Advantages and disadvantages of enhanced technology

Technology	Advantage	Shortcoming
Stereo Vision Technology	Suitable for short-distance high-precision measurement	Affected by camera performance, lighting and baseline distance
Lidar ranging technology	Simple and fast	Affected by background light and diffuse reflection
Structured light technology	Wide range and high precision	Susceptible to physical optics and occlusion

It can be seen from Table 1 that structured light technology belongs to active depth imaging technology, and its core idea is the idea of triangulation. The key to structured light imaging technology is to obtain fringes with recognizable codes. The formation of these fringes will be affected by the projection distance of the light source, and different fringes will be formed due to different surfaces of the object.

In June 2010, Microsoft designed a somatosensory device called Kinect for the Xbox360 game console. Kinect is mainly composed of three parts: color camera, infrared 3D depth sensor, microphone [10]. Based on the above-mentioned infrared camera and color camera, the device can acquire depth images and color images at the same time. Multi-array microphones can collect sound information, thus providing a more powerful way of human-computer interaction.

The core component of Kinect is Prime Sensor, and the core of this component is the PS1080 system-level chip. It is precisely because of this chip that Kinect has a powerful human-computer interaction method. And Prime Sensor equipment uses optical coding technology, the key is to use the camera to obtain structured light patterns. In the entire measurement process, a COMS sensor can be completed, reducing the cost of testing.

The traditional structured light ranging technology uses structured light patterns to estimate the distance. The specific process is: first use the active light source to project the distinguishable patterns onto the objects in the scene to form different structured light patterns, and then use the camera to receive these structured light patterns reflected by the object, and analyze the position and The structured light pattern of the degree of deformation can calculate the distance from the object to the camera. The Light Coding technology l38 used by Kinect is a kind of structured light technology, but the difference from the traditional structured light technology is that Light Coding is realized through a technology called "laser speckle" [11].

Laser speckle has high randomness and is very sensitive to the change of distance. In other words, in the scene to be tested, the shape or size of speckle pattern in any two regions is different. If you want to obtain the "speckle pattern" of the whole scene to be tested, that is, some mark is made on the distance information of the whole scene to be tested, so that the distance information of an object in the scene to be tested can be converted into the "speckle pattern" of the object. Through the "speckle pattern" you can get the specific location information of the object in the scene. Therefore, the light source needs to be calibrated to obtain all speckle patterns of the scene to be measured, as shown in Fig. 2.

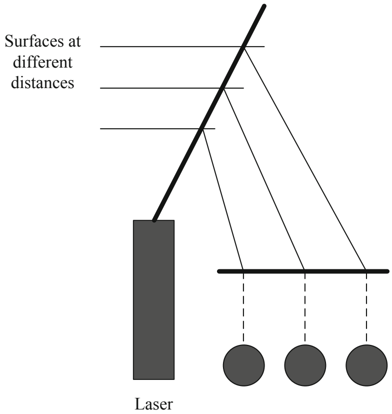

Fig. 2. Principle of speckle pattern formation

It can be seen from Fig. 2 that the used light waves formed by the interference between multiple light waves have different frequencies and have different phases and amplitudes. The speckle pattern is actually a random diffraction pattern. Laser speckle uses the higher coherence of laser light to make the diffraction result more prominent. The information recorded by the speckle image contains information about the light and the objects that the light can pass through, and the speckle images of any two regions in space are different. Therefore, people use this feature to measure the roughness of the reflective surface, the movement speed of the object, and the electronic speckle photography technology and electronic speckle interferometry used in the industrial field.

The speckle pattern can reduce the optical complexity of the projection system to a large extent, the reason is that its measuring depth is very large, generally about a few meters. Assuming that the distance between the object and the camera is Z, the average vertical and horizontal dimensions of the speckle here are as follows:

$$S_L = \lambda \left(\frac{Z}{\phi} \right)^2 \tag{1}$$

$$S_T = \frac{\lambda Z}{\phi} \tag{2}$$

In the formula, λ represents the wavelength of the emitted light, and ϕ represents the size of the diffuser. When Kinect works, the COMS sensor receives the infrared light reflected from the object. Some areas in the depth image appear black, and the depth value is zero. In fact, the sensor does not receive the reflected speckle pattern.

2.2 Independently Adjustable Design Point Cloud Registration Algorithm Based on Sparse Coefficient

The super-resolution reconstruction of a single image can be defined as the process of generating a corresponding high-resolution image by adding more details and resolution on the basis of the original low-resolution single input image, and generating a high-resolution image from the low-resolution input image through a predetermined mathematical model. The pixel intensity value obtained by the weighted average interpolation method is locally similar to that of adjacent pixels, which can generate a better smooth region, but it does not perform well when high-frequency regions such as edges produce large gradients [12]. The high score image is reconstructed by using the image prior information learned from the edge features. Edge is an important original image structure, which plays a decisive role in visual perception. Because the prior information is learned from the edge, the reconstructed image has high edge quality, appropriate sharpness and less artifacts. However, the effectiveness of edge a priori in modeling other high-frequency structures is poor.

With the introduction of machine learning and compressed sensing theory, learning-based super-resolution algorithms are increasingly used in single-image super-resolution applications [13]. This paper proposes a sparse coding super-division method based on sparse coding and dictionary learning. The edge sharpness of the super-division image is better but the artifacts are more obvious. The joint dictionary training generates a complete dictionary and proposes a method to build a sample library based on the redundant information of the image itself. The sample library is generated by interpolation, but the adaptive ability is poor. The training of the high-score dictionary and the low-score dictionary are carried out separately, the dimensionality of the image block is reduced, the neural network approximation is introduced and the training of the high-score dictionary is simplified with the pseudo-inverse, which improves the over-score speed. The dictionary learning is no longer limited to small-scale, definite training samples, and the accuracy of dictionary training is improved, and the application effect of image restoration is better. The super-resolution reconstruction based on ODL is compared with other algorithms, but the improvement effect is limited. Double sparse coding in the wavelet domain, the reconstruction effect is better. Combining the advantages of reconstruction and learning methods, a multi-level dictionary super-resolution reconstruction algorithm based on image pyramid is proposed. The learning-based super-score algorithm represented by the SCSR method can achieve a better single-image super-score effect. If it can effectively suppress the edge artifacts and increase the texture details, the super-score effect will be greatly improved.

In view of the problems in obtaining depth images by Kinect, many researchers have proposed methods to repair depth data, but many methods benefit from the traditional depth data repair algorithms. In view of the noise phenomenon and low resolution of traditional depth data, the traditional depth data repair algorithm has a good enhancement effect. However, for Kinect's strong noise and large area loss, the traditional depth data enhancement algorithms need to be improved. Therefore, these traditional algorithms have great reference value for the research of depth data restoration based on Kinect. The following briefly introduces the main two types of algorithm principles and their representative algorithms, namely, depth data enhancement algorithm based on local information and depth data enhancement algorithm based on global optimization.

The basic idea of depth image enhancement algorithm based on local information is to calculate it through the similar pixel with depth data [14]. Most of these algorithms are based on linear transformation. Let p and q denote two pixels and their positions in the image, and h denotes the weight coefficient of the pixels in the neighborhood, then the output image is as follows:

$$g(p) = \sum_{q \in N(P)} h(p-q)f(q) \tag{3}$$

Among them, h in the linear transformation is generally constant in the entire image. In order to facilitate the calculation of the center of gravity of the neighborhood, a matrix with an odd number of rows and columns is generally used to represent h.

In practical applications, many methods only use the information of one image, and use the information as a guide to filter the secondary image, that is, for different pixels, the guided image will form different filter cores. Bilateral filtering is composed of two sub-filter cores, one is related to spatial distance, called spatial domain weight, and the other is related to pixel value difference, called range weight. The output J of bilateral filtering at point p is as follows:

$$Jp = \frac{\sum_{q \in N(P)} s(p-q)r(I_P - I_q)I_q}{g(p)} \tag{4}$$

$$p = \frac{s(p-q)}{g(p)} \tag{5}$$

$$r(I_P - I_q) = \exp\left(-\frac{\left\|I_P - I_q\right\|^2}{2\sigma_r^2}\right) \tag{6}$$

In the formula, I_P, I_q represents the color value of the pixel, and σ_r represents the range parameter of bilateral filtering. The weight coefficient of the bilateral filter is inversely proportional to the spatial distance or the difference in pixel value. This feature makes the bilateral filter have the advantage of keeping the edges better. Since the filtering kernel of bilateral filtering is calculated based on the guided image, it is not constant during the filtering process of the entire image. In traditional bilateral filtering, the leading image is the original image. Subsequent researchers replaced the guided image with another image that was different from the original image, thereby obtaining a joint bilateral filtering algorithm. For the repair of the black hole in the depth image, the color image is usually used as the pixel value difference degree for calculation, and the black hole in the depth image is used as the filtering object, thus the following formula is obtained:

$$E = \exp\left(-\frac{I_P - I_q}{\sigma_r}\right) \tag{7}$$

$$E(x) = \frac{1}{E} = \frac{1}{\exp\left(-\frac{I_P - I_q}{\sigma_r}\right)} \tag{8}$$

$$J(p) = \frac{\sum_{q \in N(P)} s(p-q) r(I_P - I_q)}{\sum_{q \in N(P)} f(q)} \tag{9}$$

$$J(X) = \frac{\frac{I_P - I_q}{\sigma_r}}{\sum_{q \in N(P)} s(p-q) f(q)} \tag{10}$$

Compared with the depth image enhancement algorithm based on local information, the depth image enhancement algorithm based on independently adjustable coefficients can retain more global information. The depth image enhancement algorithm based on local information converts the input image into the expected result through the local image repair operator. In order to obtain the ideal image processing effect, the depth image enhancement algorithm based on global optimization constructs the global energy term according to the image information and some limited conditions. One of the most popular ideas in this kind of methods is based on Markov random field model. The method based on the model constructs the maximum likelihood term based on the difference between the input image and the estimated image and the prior constraints that the latter needs to meet, so as to construct the final probability expression of the model and obtain the maximum value of the probability.

In fact, in the methods based on global optimization, it is a common method to solve the image processing problem by introducing regular terms. The method based on this idea has a great relationship with the image enhancement method of the above model. Its data item corresponds to the maximum likelihood item in the above model, and its smoothing item corresponds to the a priori item in the above model. Generally, researchers equate the above two. As mentioned above, in solving problems such as sparse image interpolation, image noise reduction, filling invalid pixels of the image, giving priority to the image enhancement method based on global optimization can obtain a good repair effect.

2.3 Color 3D Image Surface Reconstruction

Surface representation is the most basic method to represent the shape of three-dimensional material. It can provide comprehensive information of three-dimensional objects. There are two specific forms: boundary contour representation and surface surface representation.

The initial surface reconstruction method adopts the description method based on contour line, that is, in the sectional image, the deterministic segmentation of the target contour is realized manually or automatically, and then the contour lines of each layer are "stacked" to represent the boundary of the object of interest. This contour line representation method is simple and the amount of data is small, but it is not very intuitive. In addition to representing the object by contour, it can also be represented by the surface of the contour reconstructed object. The earliest method is based on polygon technology, mainly using the triangle algorithm of plane contour, fitting the surface of this group of surface contours with triangles, and solving the problem of three-dimensional connectivity of a series of surface contours. The surface of the object is formed by filling the small planes of triangles or polygons between the adjacent boundary contours, and the result is only a piecewise smooth surface. Firstly, determine a surface threshold, calculate the gradient value in each voxel, compare it with the surface threshold, find out those cubes containing surfaces, and use the interpolation method to calculate these surfaces, which is actually the process of extracting isosurfaces.

The main advantage of the surface-based method is that it can be displayed using more mature computer graphics methods. The amount of calculation is small and the running speed is fast. With the help of dedicated hardware support, drawing on a high-performance PC can completely realize real-time interactive display.

Because volume rendering directly studies the relationship between light passing through the volume data field and voxels, there is no need to construct an intermediate plane, and many detailed information of the voxels are retained, and the fidelity of the results is greatly improved. In terms of the quality of the resulting image, volume rendering is better than surface rendering. But in terms of interactive performance and algorithm efficiency, at least on the current hardware platform, surface rendering is better than volume rendering.

The surface reconstruction of tomographic data is to deduce the spatial structure of the corresponding entities from the contour lines on a series of sections. In order to ensure the correctness and uniqueness of the derivation, the boundary of the entity is required to be composed of two-dimensional points, and the intersection of the entity and the plane is required to be two-dimensional. These assumptions are reasonable. The entire surface regroove process can be divided into two steps, topology reconstruction and geometric reconstruction. The former derives the topological representation of the entity, and the latter establishes the geometric representation of the entity.

The purpose of topology reconstruction is to classify the contour lines on each fault in the three-dimensional tomographic data set, confirm the entity to which each contour line belongs, and ensure the correctness of the reconstruction. Therefore, topological reconstruction is the basis of tomographic data reconstruction. When there are multiple contour lines, it means that there will be entity intersections, the problem is more complicated, and it is more necessary to reconstruct the topology first.

The classification of contour lines is described by a classification map. Each vertex of the classification map corresponds to a contour line, and its edges are connected to two contour lines belonging to adjacent layers. If there is an entity described by the classification map, the classification map is considered valid. In other words, a valid classification map corresponds to entities that meet the conditions.

Linear smoothing filter is suitable for many situations and its design is simple, which makes it an important method in signal processing, especially for signal spectrum and noise spectrum with obvious differences. However, for the signal with a wide spectrum, that is, the steep edge in the general sense, although the linear smoothing filter can smooth the noise, it will also blur the steep edge. At the same time, for impulse noise, the linear filter can not be completely smooth. Therefore, in most cases, median filter is used to solve the above problems. However, due to the lack of large-area depth pixels in the depth image, the repair effect of median filter is very poor. Therefore, the iterative idea is added to median filter to make the improved median filter suitable for the lack of large-area depth pixels. On this basis, guided by image edge information and color image information, the detailed characteristics of image edge are guaranteed.

In the depth image obtained by Kinect, most of the positions of black holes are located at the edge of the object. It is difficult to accurately find the depth value only by using the color image information. To solve this problem, a depth image enhancement algorithm based on edge information guided filtering is proposed in this paper. Firstly, the edge of color image and depth image is extracted to obtain color edge image and depth edge image. The color edge image and depth edge image are enhanced respectively, and the enhanced edge image is fused to obtain the edge image as a guide; Then, guided by the fused edge image, the iterative median filter is used to fill the black hole; Finally, the adaptive median filter is used to smooth the noise of the image.

There are real edges and wrong edges in depth edge image. The pixels in the black hole area in the depth image are called invalid pixels. The invalid pixels are zero, and the effective pixels are greater than zero. In order to determine these two edges, it is necessary to detect the neighborhood pixel of an edge pixel in the depth edge image. If there is no invalid pixel, this pixel is the real edge pixel. If there is an invalid pixel, this pixel is the pixel of the wrong edge. Although the wrong edge is not the real edge of the object, it can provide a guide to find the real edge of the object in the black hole part.

When looking for the real edge in the black hole area, for each invalid pixel, calculate its vector gradient, the calculation method is the same as the above calculation of the color edge image pixel vector gradient. The boundary of the object in the black hole area always has two edges, so the pixel can be found on the other wrong edge. Through this method, the two boundaries around the black hole in the depth edge image are enhanced, thereby enhancing the depth edge image.

Through the above steps, an enhanced color edge image and an enhanced depth edge image are obtained respectively. In order to obtain more accurate image edge information, the enhanced edge image is fused. Since the edges of color images are more reliable, color edge images are the main ones. If a certain part of the color edge image is unreliable, then the edges of the depth edge image are used. The specific method is as follows: For the enhanced depth edge image, first calculate the vector direction of each pixel. If the edge of the color edge image is close to this direction, the edge of the color edge image is used, and the edge of the depth edge image is discarded, otherwise it will be The edge of the deep edge image replaces the edge of the color edge image. By fusing the enhanced color edge image and depth edge image, more accurate image edge information is obtained, which provides favorable guiding conditions for subsequent image processing.

3 Experiment and Analysis

In order to test the application effect of the color 3D image surface reconstruction method based on the independent adjustable sparse coefficient designed in this paper, it is compared with the traditional 3D image surface reconstruction method, and the following experiments are carried out.

3.1 Experiment Preparation

Using the ray projection algorithm, in the Windows environment, combined with the MFC and MITK platform to realize the volume rendering reconstruction of the image, and the reconstructed image can be observed in various directions. After setting different opacity, the volume reconstruction image with different transparency is obtained. At this time, the experiment process is shown in Fig. 3.

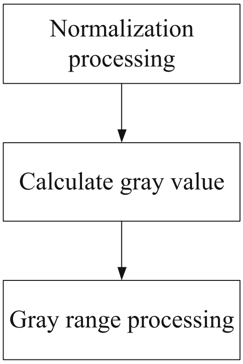

Fig. 3. Image reconstruction process

Relevant experimental parameters are shown in Table 2.

Table 2. Experimental parameters

Project	Parameter
Training data set	DIV2K data set
Number of images	500
Rebuild times	80
Operating environment	Windows 10

3.2 Experimental Results and Discussion

The color three-dimensional image surface reconstruction method designed in this paper and the traditional color three-dimensional image surface reconstruction method are used for three-dimensional reconstruction respectively, and the three-dimensional reconstruction indexes of the two methods are calculated using formulas (3)–(8).

The calculation results are shown in Table 3.

Table 3. Experimental results

Rebuild times/time	Reconstruction index	Traditional method reconstruction index
10	0.954	0.456
20	0.964	0.534
30	0.978	0.521
40	0.995	0.498
50	0.934	0.561
60	0.934	0.663
70	0.948	0.574
80	0.957	0.642

By analyzing the results shown in Table 3, it can be seen that with the increase of the number of image reconstruction, the reconstruction index of both the proposed method and the traditional method presents a trend of constant change. The reconstruction index of the traditional method varies between 0.456–0.663, while the reconstruction index of this method varies between 0.934–0.985. In contrast, the reconstruction index of the 3d image surface reconstruction method designed in this paper is higher, indicating that the reconstruction effect of the method proposed in this paper is good and has certain application value.

4 Conclusion

With the continuous development of scientific research technology and the continuous improvement of people's quality of life, 3D reconstruction technology has become the focus of current research. How to achieve high precision scene reconstruction has become a hot topic in the field of computer vision. There are several key steps in the process of 3D reconstruction. In this paper, the problems of depth image enhancement and point cloud registration are studied deeply, and relevant improvement methods are proposed.

In this paper, based on the idea of global optimization and guided by edge information, iterative median filter is used to estimate the depth pixel value. Finally, adaptive median filter is used to reduce the noise, so that the obtained restoration results have more complete global structured information and clearer edges.

The experimental results show that the proposed method achieves good reconstruction effect and is more suitable for practical application.

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