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Improved SFS 3D measurement based on neural network

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Non-contact 3D surface measurement is an important problem for modern industry. Shape from shading (SFS) is a convenient method because it can recover the 3D shape only from one image. But the conventional SFS research has a lot of restriction, such as Lambertian illumination model. If the object isn't under this model, the precision will decrease quickly. We proposed an improved SFS based on neural network combining with genetic algorithm. This proposed SFS doesn't care much about the illumination and increased the precision. It has been used in the 3D reconstruction of synthetic vase, and also used in the online 3D measurement of work piece.

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1. Introduction

Research on 3D measurement has become an urgent requirement for modern industry, because it can give more exact estimation about the quality of product. Among all the existing 3D measurement method, non-contact optical 3D measurement has become more and more popular. Most of present 3D optical methods, need to obtain the geometrical information relate to the measured parts, such as structure light method, which uses laser or visual light to form structured light point, structured light strip, structured light plane, or structured grating. Now structure light has been commonly used in steel and car industry to inspect the dimensions of some key point. But the operation of structure light is very complex, expensive, and difficult to complete 3D online shape measurement. So 3D measurement with easy operation and low cost should also be exploited. Moreover, the 3D recovery of from a historical image should also be considered.

SFS is a process to reconstruct the 3D shape information from its 2D shading image. This is an inverse problem of image formation. The cost of SFS system is very low, because it is only composed of CCD, image-collection card, and computer. The SFS technique was firstly suggested by Horn [1] and further studied with his colleague. The solution of the SFS was proved to be robust and stable under a controlled environment [2]. Since the reflectance model is nonlinear in terms of the surface gradients, certain restrictive assumptions have to be made in order to solve the SFS problem. Firstly, surface reflection is generally assumed to be diffuse reflectance. Secondly, a distant point light source is assumed to be known. Thirdly, images are formed by orthographic projection. Based on these assumptions, a simple Lambertian model was established such that apparent distortions on reconstructed surfaces often result in many practical applications. Torrance-Sparrow model [3] assuming that a surface is composed of small, randomly oriented, mirror-like facets. Wei and Hirzinger used a feed forward network to parameterize the object surface, but their performance would be degraded by using ineffective gradient-descent method that is of slow convergence and prone to the local minima problem, especially for a complex SFS problem [4]. Cho and Chow [5] proposed an improved neural SFS learning algorithm to tackle the shortcomings of the Wei and Hirzinger's approaches. This SFS algorithm could enhance the solving of the SFS problem in terms of the reconstruction speed and the quality o solutions, but it is still under the restrictive condition of the Lambertian model, where the light source direction must be given. In 2000, Cho and Chow present a novel SFS neural-learning-based reflectance model [6], under which, the viewing direction and the light source direction are no longer required. But the optimization of weight suffers from the well-known local minima problem.

It is the purpose of this paper to propose an efficient solution to SFS, which can realize robust and high precision 3D measurement only from one image. The image can be a historical picture, or captured by CCD or camera. Compared with conventional SFS, the proposed method doesn't care much about the direction of the light source, and can reach high precision. The structure of this paper is as follows. In section 2, a neural-based reflectance model for SFS, combined with genetic algorithms, is studied. In section 3, the precision of 3D measurement of synthetic vase is analyzed. In section 4, the application in the 3D measurement of work piece is introduced. The last is for the conclusion.

2. Neural-based reflectance model for SFS

SFS is well worked for Lambertian reflectance model. However, in most practical cases, the intensity and direction of illumination is uncertainty. In order to generate a much more practical reflectance model, incorporating more physical reflectance parameters and effects, is inevitable. It is very difficult to solve the nonlinear equation of a very complicated SFS model. Because the reflectance model can be viewed as an arbitrary continuous function, we proposed a neural network framework to provide the approximation of the reflectance model. The proposed neural-based model is able to approximate any real-value continuous function. The variables of reflectivity (i.e., the entire factors which are dependent on the brightness) are simplified and tuned by the self-learning weights with the nonlinear activation function. This neural-based model has a significant advantage over the conventional model, in that a proper reflectance model is obtained despite the illuminate condition being unknown.

Suppose that a single-hidden-layer network, defined as mapping function G(□), is used and let $\beta_{i,j} = (p_{i,j}\ q_{i,j}\ 1)^T$ be an input vector of the network. Let $\sigma(\cdot)$ be a bounded and monotone-increasing continuous activation function and Ω_{p-q} denote the (p,q) -dimensional space. The space of continuous functions on Ω_{p-q} is denoted by $C(\Omega_{p-q})$, then given any function $R \in C(\Omega_{p-q})$ such that the mapping function $G(\cdot):\Omega_{p-q} \to \Re$, there exist sets of real values v_k and w_k, where $k = 1,\cdots,N.$ Based on the universal approximation theorem, the proposed reflectance model is defined as formula (1).

$$R_{i,j}(p,q) = G(W,v;\beta_{i,j}) = \sigma(\sum_{k=1}^{N} v_k \sigma(W_k \beta_{i,j}) + \theta) \qquad (1)$$

Where $W = (w_1,\cdots,w_N)^T$ denotes the weights matrix connected between the input and the hidden layer, $v = (v_1,\cdots,v_N,\theta)^T$ denotes the weights (v) and the bias (θ) connected between the hidden layer and the output layer, and N is the number of the hidden units. The activation function is in a form of $\sigma(x) = 1/1+\exp(-x)$. In this formulation, the light source vector is not required because the trained network weights are able to represent the proper reflectance model based on the object orientation information. In solving the SFS problem by this neural-based model, the cost function is commonly used as formula (2).

$$E_T = \iint_{\Omega} (I - G(W,v;\beta))^2 + \lambda((\frac{\partial p}{\partial x})^2 + (\frac{\partial p}{\partial y})^2 + (\frac{\partial q}{\partial x})^2 + (\frac{\partial q}{\partial y})^2)dxdy \qquad (2)$$

The first term is the intensity error term and the second term is a smoothness constraint that is given by the sum of the spatial derivatives of p and q. λ is a scalar that assigns a positive smoothness parameter.

Based on this objective function, the weights of the neural based reflectance model and the object surface gradients are determined by performing a unified learning mechanism. Through the learning process, the neural network weights and the surface gradients are computed iteratively where the weights are optimized by a specific learning algorithm and the surface gradients and depth are evaluated by the conventional SFS method. In solving the SFS problem, the variation method is used to calculate the solutions of the surface gradient *(p, q)* and the object surface depth *z* on the discrete grid. Also, instead of determining the physical reflectivity parameters of the neural-based reflectance model, the neural network weights are optimized to generalize the proper reflectance model. Conventionally, the optimization method is usually based on the supervised learning process by using gradient-descent methods, which suffer from the well-known local minima problem. Genetic algorithm is used to find the overall minima point. The whole neural-based method can be described in Fig. 1.

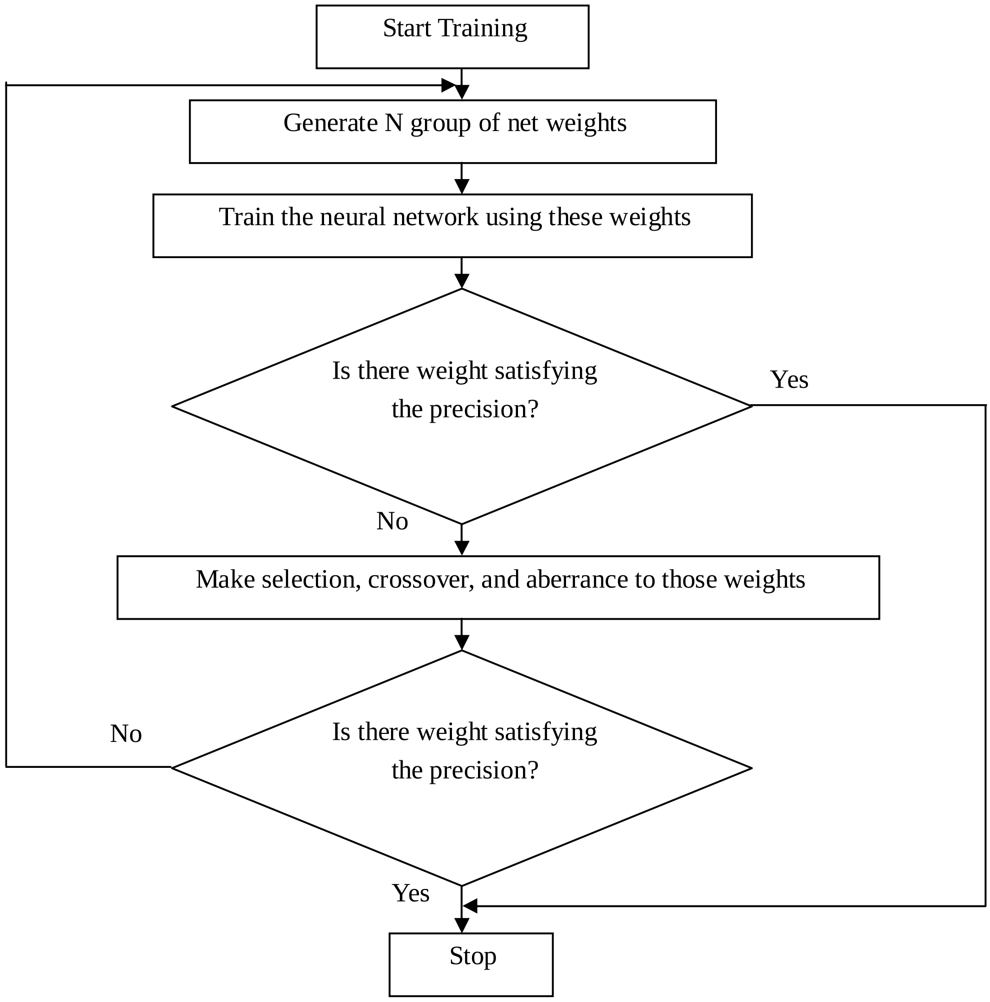


Fig. 1. The whole procedure of SFS method based on neural network and genetic algorithm.

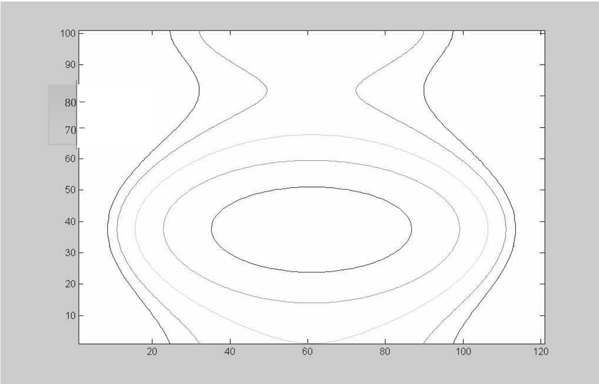
3. Precision analyze of 3D measurement by synthetic vase

One synthetic vase was selected to test the precision of the proposed SFS method. The true depth maps of the synthetic, were generated mathematically by the following function:

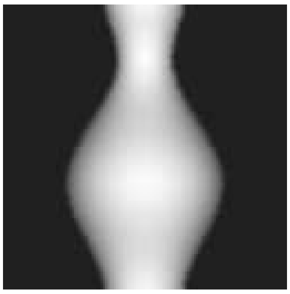
$$z(x,y)=\sqrt{[0.15-0.1y(6y+1)^2(y-1)^2(3y-2)]^2-x^2} \quad (3)$$

Where $-0.6 \le x \le 0.6$ and $0.0 \le y \le 1.0$.

The synthetic object was generated using true depth maps by 3D numerical control machine. The contour plot of this function is shown in Fig. 2(a).



(a)



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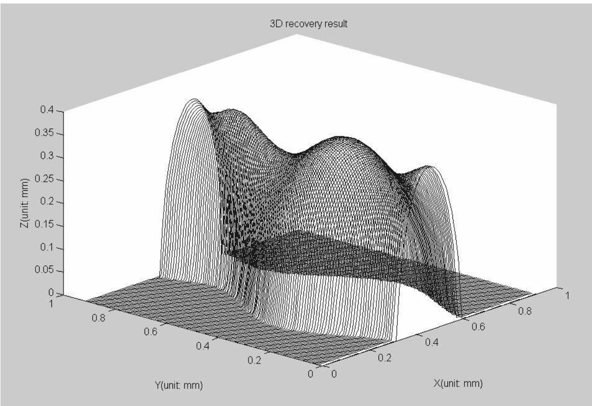

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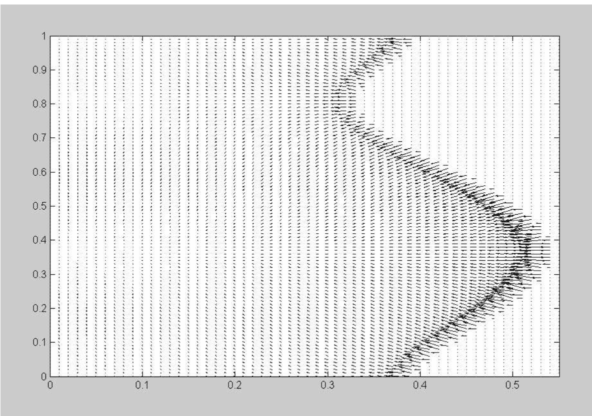

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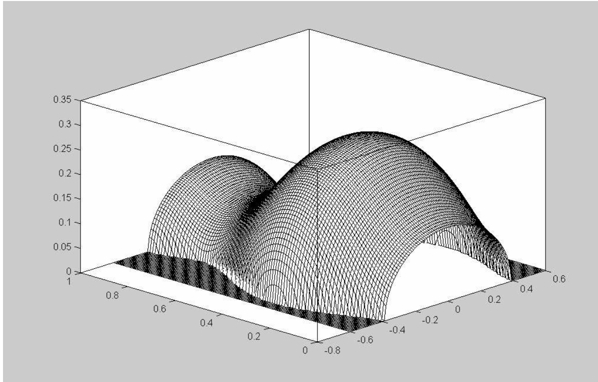


(e)

Fig. 2. Sequence images of synthetic vase.

- *(a) The contour plot of vase using its forming function;*
- *(b) The image of synthetic vase captured by CCD;*
- *(c) Poor 3D recovery using conventional SFS;*
- *(d) A part of gradient plot using the proposed SFS method based on neural network;*
- *(e) 3D shape recovery using the proposed SFS.*

Different illuminate conditions (i.e., known illuminate directions and unknown directions) were employed to verify our SFS method based on neural network. Fig. 2(b) shows the image captured by CCD with light source direction of $\Phi=90^{\circ}$ and $\theta=0^{\circ}$, where Φ is the slant of light source, and θ is the tilt of the light source. The image size of Fig. 2(b) is 128×128. If neural network doesn't adopt, the performance of the SFS is very poor, which is shown in Fig. 2(c). When using our proposed SFS base on neural network, the gradient *(p, q)* image will be quickly plotted. One part of the gradient image is shown in Fig. 2(d). In order to plot the 3D surface of the synthetic vase, the gradient *(p, q)* must be transferred to the true depth *z*. The relation between *(p, q)* and *z* is shown in formula (4).

$$p=\frac{\partial z}{\partial x},\quad q=\frac{\partial z}{\partial y} \tag{4}$$

Where ∂x and ∂y represents the minimal step in x and y coordinate. For a image with certain size, the minimal step of x and y coordinate is the distance between two neighbor pixel. If the X coordinate size of measured object is Lx, and it contains *Nx* pixels in this direction. Then ∂x can be acquired by the division between *Lx* and *Nx.* According to these relationships, the depth z of each pixel can be computed. Fig. 2(e) plots the recovered 3D surface, which has been greatly improved compared with conventional SFS. It is shown that the reconstructed surfaces are very close to the true height map of the objects. The reconstructed depth error compared with conventional SFS from different light source direction is listed in Table 1. It is shown that the light source direction of $\Phi=90^\circ$ and $\theta=0^\circ$ is the best illuminate direction. If the light source direction is unknown, the absolute depth error is also satisfied.

Table 1. Comparison of depth error between the conventional SFS and the proposed SFS from different light direction.

Illumination directions	Absolute depth error (unit: mm)					
	Conventional SFS			SFS based on neural network		
	Mean	Max	Std.	Mean	Max	Std.
$\Phi=0^\circ$ $\theta=0^\circ$	0.132	0.778	0.111	0.052	0.512	0.049
$\Phi=45^\circ$ $\theta=0^\circ$	0.125	0.589	0.129	0.051	0.500	0.037
$\Phi=90^\circ$ $\theta=0^\circ$	0.059	0.451	0.058	0.007	0.011	0.002
$\Phi=135^\circ$ $\theta=0^\circ$	0.122	0.378	0.134	0.049	0.047	0.044
$\Phi=225^\circ$ $\theta=0^\circ$	0.158	0.698	0.142	0.053	0.055	0.058
Unknown1	0.178	0.574	0.155	0.044	0.049	0.041
Unknown2	0.198	0.855	0.129	0.048	0.053	0.047

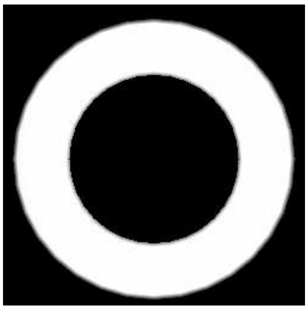
4. Applications of proposed SFS in the measurement of work piece

Online 3D surface measurement of work piece has become more and more important in modern industry, because it can give vivid information about the status of the work piece and the quality of product can be easily judged. Although a lot of researches using different technique has been focus on 3D research, but now there is no excellent instrument really used in the industry, for the purpose of automatic 3D surface defect detection. Some 3D methods will bring hazard to people. For example, X-ray technique directly harms people's body. Eddy current will cause waste of resource. So because of the limitation of former 3D research, robust 3D measurement method should also be exploited. The proposed SFS method is suit for the online 3D measurement. Its hardware is composed of CCD, lighting, image-collection card and computer, which are commonly used in modern image collection system. CCD is a general non-contact measurement sensor, which is low cost and high reliability.

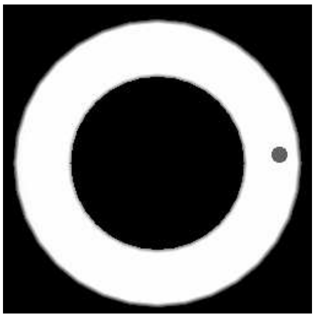
Two image of work piece is shown in Fig. 3(a) and Fig. 3(b), their image size are all 252×252. The standard dimension in Z direction is 20 mm. Fig. 3(a) is a work piece without obvious defect. Fig. 3(b) is a work piece with a dot defect. Using the proposed SFS, they are all recovered, as shown in Fig. 3(c) and Fig. 3(d). A part of the 3D data in the defect region is listed in Table 2. From the 3D data, defect or non-defect work piece will be easily detected.

Table 2. Some 3D dimension data of the defect in a work piece.

ID	Measurement value (unit: X：mm，Y：mm，Z：mm)								
1	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	6.250	6.250	6.250	6.250	6.250	6.250	6.250	6.250
	Z	16.822	15.701	16.262	15.140	12.056	14.953	11.121	1.869
2	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	6.406	6.406	6.406	6.406	6.406	6.406	6.406	6.406
	Z	14.019	14.393	17.664	17.009	13.925	12.710	12.075	3.178
3	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	6.563	6.563	6.563	6.563	6.563	6.563	6.563	6.563
	Z	18.692	17.757	15.047	13.738	12.710	14.299	11.869	2.091
4	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	6.719	6.719	6.719	6.719	6.719	6.719	6.719	6.719
	Z	18.692	15.047	13.084	13.832	17.850	17.850	14.323	7.654
5	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	6.875	6.875	6.875	6.875	6.875	6.875	6.875	6.875
	Z	8.972	17.664	14.860	10.935	10.935	9.439	12.336	9.333
6	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	7.031	7.031	7.031	7.031	7.031	7.031	7.031	7.031
	Z	9.8131	17.757	10.561	9.4393	11.682	12.991	15.514	15.981
7	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	7.188	7.188	7.188	7.188	7.188	7.188	7.188	7.188
	Z	19.252	18.411	14.299	18.692	17.009	19.346	17.383	4.579
8	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	7.344	7.344	7.344	7.344	7.344	7.344	7.344	7.344
	Z	19.439	19.626	19.252	19.159	17.757	19.720	17.477	3.925
9	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	7.500	7.500	7.500	7.500	7.500	7.500	7.500	7.500
	Z	19.533	19.533	19.720	18.318	11.776	12.991	12.523	4.589
10	X	15.625	15.781	15.938	16.094	16.250	16.406	16.563	16.719
	Y	7.656	7.656	7.656	7.656	7.656	7.656	7.656	7.656
	Z	18.505	19.346	15.140	17.290	19.533	7.757	8.911	6.065



(a)



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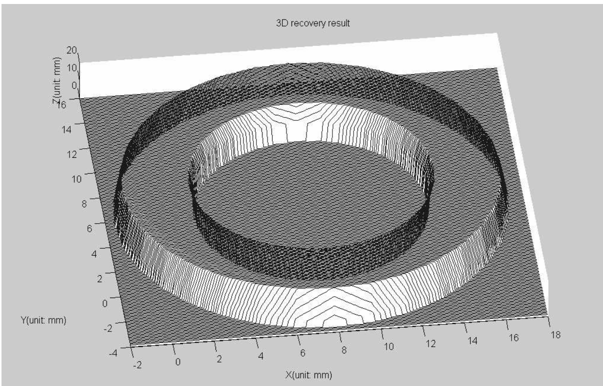

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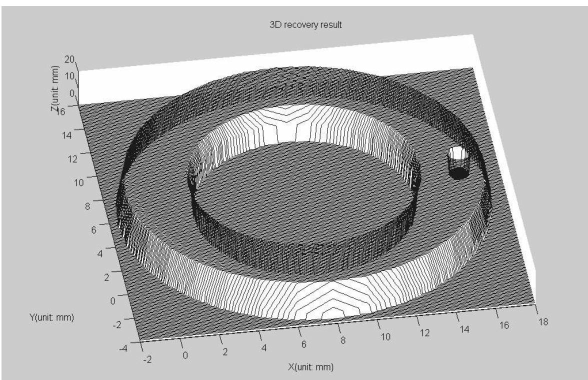

(d)

Fig. 3. Sequence images of work piece.

(a) Image of non-defect work piece;
(b) Image of work piece with a little dot;
(c) 3D recovery of the non-defect work piece;
(d) 3D recovery of the work piece with little defect.

5. Conclusions

SFS technique can reconstruct the 3D shape of object based on single image. But conventional SFS suffer from low precision when the measured object isn't under the Lambertian model. We proposed an improved SFS based on neural network combining with genetic algorithm, which doesn't care much about the light source direction. Through the neural network model, the SFS algorithm has become more robust and effective for most application. The precision of the proposed SFS has been verified, by the application about 3D reconstruction of synthetic vase. And the proposed SFS has been successfully used in the 3D online measurement of work piece. The advantages of the proposed SFS are as follows:

(1) Non-contact and non-destructive technique (NDT). No harming to the work piece. CCD or camera performs the capture of the 3D data, which just like our eyes looking on the work piece, with on touching on it.
(2) No harming to operator and no harming to environment. Unlike X-ray technique and eddy current technique, the working voltage of proposed SFS is just 12V or 24 V. It is in the safe voltage range, which cannot bring electrocute to people.
(3) Easy operation. If the image has been clearly transferred to computer, computer will do all the work of 3D reconstruction. No measurement of distance is needed.
(4) Local cost. All the equipment used in this system is common product, and can be easily bought.
(5) More robust. Compared with conventional SFS, it doesn't require the knowledge of illumination and restrictive assumptions.
(6) High precision. Compared with conventional SFS, the precision of the 3D recovery has been great improved.
(7) Applicable: Because of the above advantages, the SFS based on neural network can be used in practical industrial applications and complete 3D online measurement.

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