Research Article

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Interactive 3D reconstruction method of fuzzy static images in social media

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Abstract: Because the traditional social media fuzzy static image interactive three-dimensional (3D) reconstruction method has the problem of poor reconstruction completeness and long reconstruction time, the social media fuzzy static image interactive 3D reconstruction method is proposed. For preprocessing the fuzzy static image of social media, the Harris corner detection method is used to extract the feature points of the preprocessed fuzzy static image of social media. According to the extraction results, the parameter estimation algorithm of contrast divergence is used to learn the restricted Boltzmann machine (RBM) network model, and the RBM network model is divided into input, output, and hidden layers. By combining the RBM-based joint dictionary learning method and a sparse representation model, an interactive 3D reconstruction of fuzzy static images in social media is achieved. Experimental results based on the CAD software show that the proposed method has a reconstruction completeness of above 95% and the reconstruction time is less than 15 s, improving the completeness and efficiency of the reconstruction, effectively reconstructing the fuzzy static images in social media, and increasing the sense of reality of social media images.

Keywords: social media, blur static images, three-dimensional reconstruction, feature points

1 Introduction

Effective processing of social media information has become the most important means in the current process of informatization, ensured social security, and laid a deep foundation for the technological development [1,2]. Topics in social media are usually expressed through some social images. Image interaction in social media refers to using the real-time performance acquired by virtual reality technology to obtain social media images, giving people a sense of reality. Currently, the interactive three-dimensional (3D) reconstruction of social media images plays an important role in computer vision [3]. It exists in two-dimensional (2D) form. In order to obtain the real social media image, it is necessary to transform the 2D social media image into a 3D social media image in the 3D space to complete the social network.

The author in ref. [4] proposed the distance-gated laser imaging system to obtain the image position relationship according to the 3D imaging principle, used the binarization algorithm to solve the target image distance value, and used the centroid algorithm to compensate for the distance when the gate width is high or the laser pulse is large. The shortcomings of inaccurate information are to obtain accurate distance information and then use motion compensation to calculate the distance information. Based on the calculation results, 3D reconstruction of social media images is performed. Finally, the simulation results show that the interactive 3D reconstruction method in this paper completes the reconstruction of static target 3D images. The result is consistent with the actual distance value. The author in [5] combined

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binocular stereo depth image information fusion technology and image 3D reconstruction technology to reconstruct social media images in 3D. First, images are collected by the camera in multiple directions, and 3D point clouds are generated according to the collected social media images. Through the binocular vision system, the normalized cross correlation (NCC) matching algorithm is used to denoise the 3D point cloud images and extract the noise reduction processing. According to the extraction results, the post-stereoscopic depth information uses a conversion method to convert the depth information corresponding to the image coordinate points into the corresponding gray values, and the conversion results are stored in the camera for image information fusion, according to the binocular stereo depth image information fusion realizes 3D reconstruction of social media images, but it is greatly affected by external factors, and the completeness of 3D image reconstruction is low, resulting in inaccurate reconstruction results. The author in ref. [6] proposed to use big data analysis technology to reconstruct the laser 3D image. First, the MapReduce algorithm is used to collect the 3D image point cloud data, and according to the collection results, the K-means clustering algorithm is used to segment the collected laser 3D image points. Reading the segmented point cloud big data, through the cloud big data, set the color, texture and other elements of the data point through the OpenGL application program interface, change the line of sight, the direction of the point of view, and reconstruct the laser 3D image. The experimental results show that the proposed method can effectively reconstruct the laser 3D image based on the large original point cloud data.

The author in ref. [7] used 3D image processing technology to reconstruct virtual images. First, the virtual image node is acquired, the image is captured according to the image node, the virtual image edge operator is calculated, and the virtual image reconstruction area is marked to obtain the reconstruction. Then the background is constructed, based on the reconstructed background, the virtual image is rendered, the image blur caused is reduced by the image texture, the image is preprocessed after rendering, the 3D reconstruction of the virtual image is completed, thus highlighting the image ratio and increasing the image quality. The simulation results verify the effectiveness of this method. Although the above two methods complete the 3D image reconstruction, they consume a long time when performing the 3D image reconstruction, and the reconstruction efficiency is low.

Aiming at the problems of the above methods, and further improving the reconstruction integrity and reconstruction efficiency, this paper proposed an interactive 3D reconstruction method for fuzzy static images of social media.

The fuzzy static images were gray media to reduce the noise interference of images. The feature points of fuzzy static images of social media were extracted by the Harris angle point detection. The RBM model was used to construct the network structure of joint dictionary learning; combining the RBM-based joint dictionary learning methods with the sparse representation models, the fuzzy static image was reconfactoried.

The experimental results show the contribution of the present method: the proposed method improves the reconstruction integrity, shortens the reconstruction time, and lays the foundation for image processing.

The innovative point of this paper lies in the reconstruction of fuzzy static images using an RBM-based joint dictionary learning method and a sparse representation model.

RBM is a generative random neural network proposed by Hinton and Sejnowski in 1986 that consists of some visible and some hidden variables that are both binary variables, that is, its state takes {0,1}, and there is no edge connection between visible cells and between hidden cells. The entire network is generally divided into input, output, and implied layers. RBM is able to reconstruct input data, which can effectively extract data features and construct new data structures for predictive analysis, and can continuously stack the features of deep neural network mining data.

The paper is organized as follows: In Section 2, the extraction of 3D reconstruction feature points is discussed. Interactive 3D reconstruction of fuzzy static images in social media are presented in Section 4. Then, simulation experiment analysis is performed in Section 3. Discussion and conclusions are presented in Sections 5 and 6, respectively.

2 Extraction of 3D reconstruction feature points

As the camera shakes when acquiring social media images, which causes the static image to be blurred, in the interactive 3D reconstruction of the social media blurred static image, it is necessary to extract the points in the social media blurred static image, which is the image feature points; the image feature points are different from the surrounding points. The more accurate the extracted result, the higher the completeness of image reconstruction and the better the reconstruction effect. Therefore, the extraction of feature points is important for the interactive 3D reconstruction of social media fuzzy static images. The extraction process of the feature points is shown in Figure 1.

As shown in Figure 1, interactive 3D reconstruction of social media fuzzy static images is of great significance, but the noise interference of social media fuzzy static image feature points in the extraction process. Therefore, gray scale processing must be performed before extracting feature points, and the processed social media static images were then extracted using the Harris corner point detection method.

2.1 Grayscale processing

Any one-time original picture, due to external interference, has a certain degree of noise interference, which has a certain impact on the completeness of the reconstruction of the fuzzy static image of social media. Social media fuzzy static image gray scale is a kind of image preprocessing. This article will gray scale the social media fuzzy static image [8–11]. The main purpose is to remove noise, eliminate various unfavorable

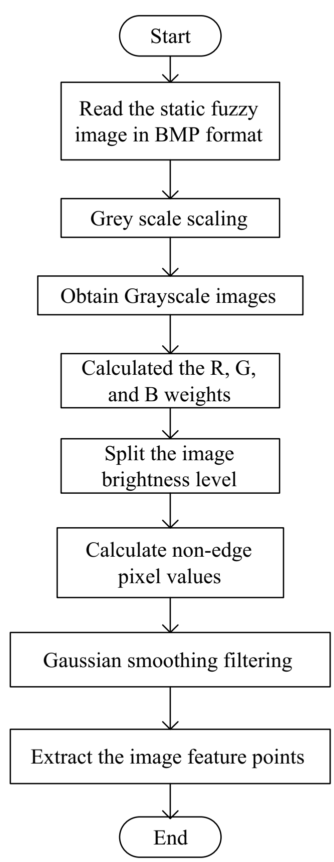

Figure 1: The flowchart of extracting the image feature points.

factors to the image, and improve the visual effect. A clear social media fuzzy static image that can reflect the original scene to the greatest extent was obtained and prepared for the subsequent feature point extraction and image reconstruction [12–15].

Image grayscale refers to social media blurring the brightness area in the static image, not the color area. After preprocessing the color area of the blurred static image of social media, the brightness of the image will be darkened, so that the gray level between the image pixels is continuous. Therefore, the image is gray scaled to obtain the grayscale image, which is divided according to the image brightness level of 0–255. 0 means that the image becomes darker, and 255 means that the image becomes brightness.

The social media fuzzy static image is saved in the BMP (Bitmap) format and read in this format. The image RGB (red, green, blue) value ranges from (0, 0, 0) to (255, 255, 255). (0, 0, 0) is all black, (255, 255, 255) is all white, and the values in between are gray values, and 256 color maps are used to represent social media blur static image gray maps [16].

In this paper, the weighted average method is used to grayscale the fuzzy static images of social media. The resulting grayscale images have better effects and more obvious changes can improve the completeness of the reconstruction of the blurred static images of social media. Image R, G, B components are set to different values; R, G, B weights are calculated, which is written as

$$R = G = B = (\mathrm{WRR} + \mathrm{WGG} + \mathrm{WBB}), \tag{1}$$

In the formula, WR, WG, WB are the weights of each component. When WR = 0.033, WG = 0.59, WB = 0.11 calculate the gray value [17]:

$$R = G = B = (0.30R + 0.59G + 0.11B). \tag{2}$$

2.2 Feature point extraction based on the Harris corner detection

After the grayscale processing of the above-mentioned social media fuzzy static image, the Harris corner detection method is used to extract the feature points of the processed social media fuzzy static image. The specific process is as follows:

(1) Using two templates, the non-edge pixel values I_x and I_y of the social media blurred static image is calculated, and the values of the four elements in M_{H} according to the pixel values is obtained. The horizontal difference template and the vertical difference template are shown in Figure 2 [18].

(2) Gaussian smoothing filtering is performed on the four elements in the obtained M_{H} to obtain a new M_{H}. The expression of the two-dimensional Gaussian filter window function is

$$w(x, y) = M_{\mathrm{H}}\frac{\mathrm{RGB}}{2\pi\sigma^2}\exp\left(\frac{1}{2\sigma^2}(x^2 + y^2)\right), \tag{3}$$

$$\begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix}$$

(a)

$$\begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$

(b)

Figure 2: Two templates. (a) Horizontal difference template and (b) vertical difference template.

in the formula, σ represents the variance.

(3) Use the four elements in M_H to calculate the magnitude of the corners of each point, the expression is

$$r(x, y) = \frac{\sum_{x,y} w(x, y) I_x^2 \cdot \sum_{x,y} w(x, y) I_y^2 - \sum_{x,y} w(x, y) I_x I_y}{\sum_{x,y} w(x, y) I_x^2 + \sum_{x,y} w(x, y) I_y^2}. \tag{4}$$

(4) According to the size of the obtained corner points of each point, extract the social media fuzzy static image feature points [19]:

$$S = r(x, y)(M_H). \tag{5}$$

Thus, the extraction of fuzzy static image is extracted and reconstructed in social media.

3 Interactive 3D reconstruction of fuzzy static images in social media

According to the feature points extracted above, interactive three-dimensional reconstruction of the blurred static image of social media is described. For the interactive 3D reconstruction of fuzzy static images in social media, this paper uses the joint dictionary learning method of the RBM network model to reconstruct the fuzzy static images.

3.1 Joint dictionary learning of the RBM network model

The RBM network model is divided into input layer, output layer, and hidden layer. The model structure of the RBM network is shown in Figure 3.

Under the condition of a certain number of units, the RBM network model will sample according to random distributed samples. It has the characteristics of discrete distribution. Therefore, all the nodes in

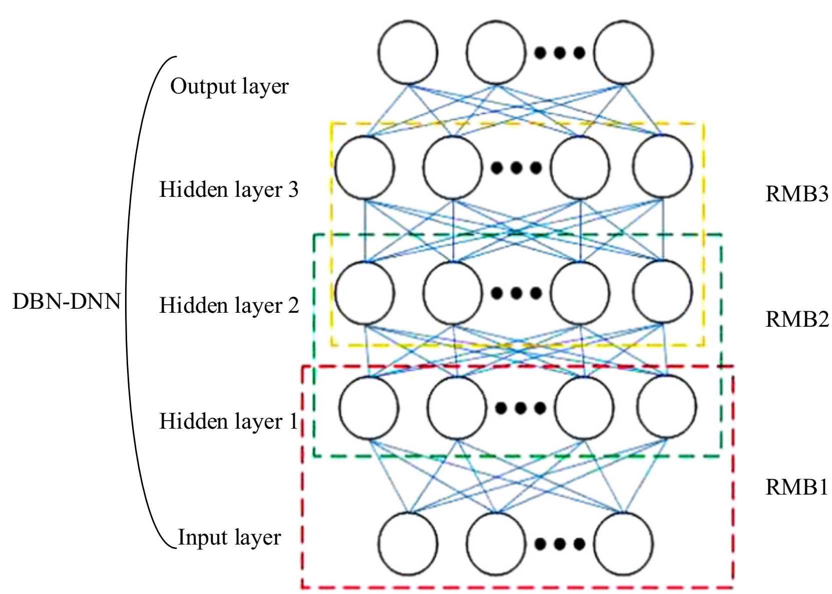

Figure 3: The model structure of the RBM network.

the hidden layer are matched with the corresponding nodes in the input layer, and the filter template is constructed in the input layer through the matched parameters, and the filter template is regarded as A base image, the base image is composed of high-resolution and low-resolution paired base atoms, so the RBM network weight parameter matrix can be used for joint dictionary learning.

Figure 4 shows the network structure of joint dictionary learning based on RBM [20].

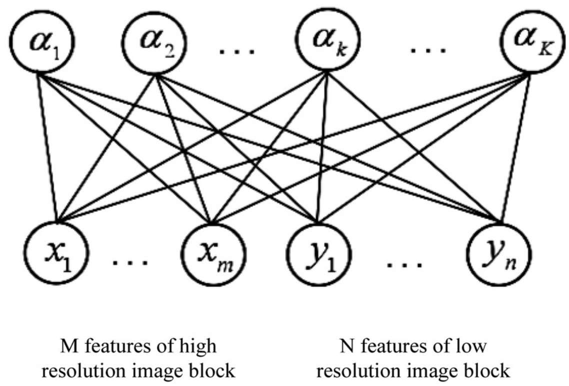

Figure 4: RBM-based joint dictionary learning network structure.

The RBM network structure is also an energy model, which uses contrast divergence parameter estimation method to learn the energy model [21–23]. The state vector of the RBM network model is set to (x, y, α), and then the model energy is calculated:

$$E(x, y, \alpha|\theta) = \sum_{k=1}^{K} S\alpha x_j y_i. \tag{6}$$

In the formula, θ represents the model parameters; x_j represents the j-th feature component of the social media blurred static image block x; y_i represents the i-th feature component of the social media blurred static image block y [24,25].

According to the calculation result of the above formula, the joint probability of all nodes in the input layer and all nodes in the hidden layer are obtained

$$p(x, y, \alpha|\theta) = \frac{\exp\{-E(x, y, \alpha|\theta)\}}{\sum_{x,y,\alpha} \exp\{-E(x, y, \alpha|\theta)\}}. \tag{7}$$

The energy model is trained, the maximum RBM network model is obtained, the log-likelihood function is established, and the contrast divergence parameter estimation method is used to learn the energy model, and then the learned model parameters can be expressed as follows:

$$\theta' = \arg\max \sum_{t=1}^{N} \log p(x, y, \alpha|\theta). \tag{8}$$

3.2 3D image reconstruction based on joint dictionary and sparse representation

After the joint dictionary learning of the RBM network model is completed, the sparse representation model can be combined to realize the three-dimensional reconstruction of the fuzzy static image of social media [26,27]. The three-dimensional reconstruction of blurred static images in social media can be divided into the following steps:

(1) Reconstruction of fuzzy static high-resolution image sub-blocks in social media

The sparse representation model is used to calculate the sparse representation vector q of the social media fuzzy static low-resolution image sub-block y, and it is expressed as

$$q = \min\|y - D_l q\| + \lambda\|q\|. \tag{9}$$

According to the calculation result of the above formula, the fuzzy static high-resolution image sub-block x of social media is reconstructed, and the expression is:

$$x = D_h q. \tag{10}$$

(2) Generation of the high-resolution initial image based on the reconstructed sub-block collage:

According to the reconstructed social media fuzzy static high-resolution image sub-blocks obtained above, all the sub-blocks are collaged according to positions to generate a social media fuzzy static high-resolution initial image X_h.

(3) Global error compensation

In the process of generating high-resolution initial images based on reconstructed sub-block collages, due to overlapping of adjacent sub-blocks, some image information is lost. For this reason [28–30], residual images are used to compensate for errors to improve social media blur, the effect, and completeness of interactive 3D reconstruction of static images.

4 Simulation experiment analysis

In order to further verify the performance of the interactive 3D reconstruction method of social media fuzzy static images in practical applications, a simulation experiment analysis is carried out. Five fuzzy social media static photos were collected from a public social media platform as experimental samples. The specific settings of the experimental samples are shown in Table 1.

The experimental equipment parameters are set as shown in Table 2.

Table 1: Experimental samples

Experimental area	**Image length (mm)**	**Image width (mm)**	**Image height (mm)**	**Image resolution (dpi)**	**Image color matching (A)**	**Image pixel (lpi)**
Sample 1	65.00	40.00	73.20	150	A1	360
Sample 2	75.60	65.00	95.00	290	A2	560
Sample 3	81.20	42.30	62.10	352	A3	263
Sample 4	93.40	60.00	56.96	121	A4	456
Sample 5	77.86	58.00	86.40	265	A5	662

Table 2: Experimental equipment parameters

Equipment	**Model**	**Function**
Host	P5VD2-X P5VD2-MX	Provide system control
Operating system	MS-DOS	Provide control function
Database	Access2010	Image data storage
Operation interface	Command-line interface	Realize user operation
Image software	CAD	Image reconstruction
Integrated system	Web Services	Complete image reconstruction

The experimental equipment is set up through the above parameters, and the social media fuzzy static image interactive 3D reconstruction method proposed in this paper, the two sets of binocular stereo depth image information fusion and 3D reconstruction methods proposed in refs. [5,6]. Based on big data analysis technology, this paper proposes a laser 3D image reconstruction method for interactive 3D reconstruction of blurred images. The simulation experiment of static images of social media to 10 times is set, and the completeness of the social media fuzzy static image reconstruction is compared according to the above five kinds of experimental samples. The comparison results are shown in Tables 3–5.

Table 3: Image reconstruction completeness of the method in this paper (%)

Experiment frequency	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
1	97.9	98	97.3	95.5	95
2	97.7	96.4	95.4	97.6	95.3
3	96	96.2	97.8	97.5	96.4
4	96	97.6	95.6	96.3	96.2
5	97.8	95.1	96.9	96.4	97.5
6	96.4	96.5	95.6	97.9	96.4
7	96.5	95.6	96.1	95.2	95.7
8	97.5	96.6	95.1	96.9	95
9	97.2	95.8	96.5	97.9	96.6
10	97.9	98	97.3	95.5	98

Table 4: Image reconstruction completeness of the method in ref. [5] (%)

Experiment frequency	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
1	93.6	94.2	90.3	91.8	94.4
2	92.4	90.9	92.9	94.8	93.8
3	92.6	94.3	91.1	90	92.7
4	91.7	93.5	92.2	95	90
5	92.5	94.9	90.9	92.5	91.6
6	91.8	94.2	91.9	93.2	94.8
7	94.1	93.9	90.9	93.3	91.9
8	94.7	94.9	92.3	92.8	91.3
9	91.3	90.7	93.1	92.1	91.2
10	91.5	91.3	93.8	92.4	91.5

Table 5: Image reconstruction completeness of the method in ref. [6] (%)

Experiment frequency	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5
1	84.2	85.6	82.3	88.8	84.3
2	82.6	81.5	84.1	85.6	88.1
3	88.2	84.6	81.2	84.6	84.3
4	81.5	81.2	82.3	82.3	81.2
5	82.4	89.2	80.4	80.4	88.5
6	81.5	84.2	81.1	81.1	81.5
7	88.6	88.5	85.2	82.3	88.6
8	87.5	81.2	84.3	81.2	87.5
9	82.6	80.7	88.1	84.3	81.2
10	91.5	91.3	93.8	92.4	91.5

According to the data in Tables 3–5, as the number of experiments increases, the completeness of interactive 3D reconstruction of fuzzy static images of social media tends to be stable. It can be seen from the experimental results that the social media fuzzy static image interactive 3D reconstruction method proposed in this paper is more than 95% complete, which is closer to 1 and satisfies the social media fuzzy static requirements for interactive 3D reconstruction of images. However, the completeness of the social media fuzzy static image interactive 3D reconstruction of the methods discussed in refs. [5,6] is significantly lower than that of the social media fuzzy static image interactive 3D reconstruction method proposed in this paper inhance completeness of 3D reconstruction greatly. It shows that the social media fuzzy static image interactive 3D reconstruction method proposed in this paper has a better effect.

In order to further verify the effectiveness of the method in this paper, the interactive 3D reconstruction time of the fuzzy static image of social media proposed in this paper, the method of ref. [5] and the method of ref. [6] are compared. Analysis and comparison results are shown in Figure 5.

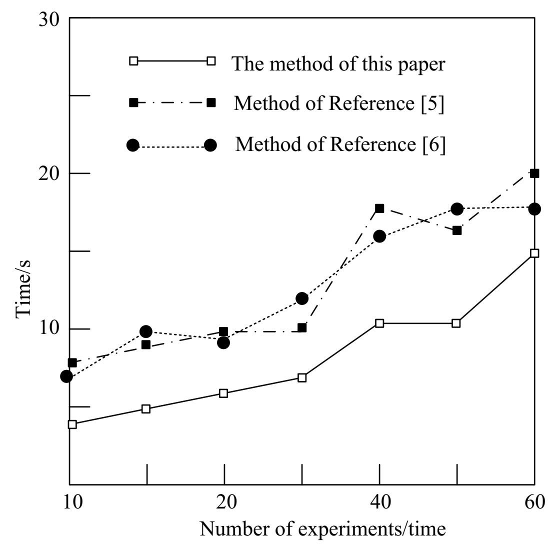

Figure 5: Comparison results of reconstruction time.

According to Figure 5, the social media fuzzy static image interactive 3D reconstruction method proposed in this paper takes less than 15 s.

5 Discussion

The experimental results show that the integrity of 3D reconstruction image proposed in this paper is better than the methods in the literature [5,6]. This is because this method uses the gray fuzzy still image to reduce noise interference, Harris corner detection method, combined with the RBM-based joint dictionary learning method, and sparse representation model to improve the reconstruction effect. The reconstruction time of the method proposed in this paper is shorter than that of refs. [5,6]. This is because this paper preprocesses the blurred image before reconstructing the three-dimensional image and uses the Harris corner detection method to extract the feature points of the preprocessed image, which lays a foundation for the subsequent rapid reconstruction of the image. The parameter estimation algorithm of contrast divergence is used to optimize the RBM network model, which improves the training speed and shortens the reconstruction time.

6 Conclusions

Because the traditional social media fuzzy static image interactive 3D reconstruction method has the problems of low completeness and long reconstruction time of the social media fuzzy static image interactive 3D reconstruction method, this paper proposes a new social media fuzzy static image interactive 3D reconstruction refactoring method. The weighted average method is used to grayscale the fuzzy static image of social media, and the processed image feature points are extracted. On the basis of the extraction results, the joint dictionary learning method of the RBM network model is innovatively used to reconstruct the fuzzy static image, and the interactive three-dimensional reconstruction method of social media fuzzy static image is designed. Simulation experiments show that the social media fuzzy static image interactive 3D reconstruction method proposed in this paper has a higher degree of completeness and better reconstruction effect, and the reconstruction time is shorter, which improves reconstruction efficiency. The proposed method lays the foundation for static fuzzy image processing and helps social media users obtain a real social media image and complete the construction of social networks.

With the continuous development of science and technology, digital image processing is more and more widely used. As a means of computer vision, image 3D reconstruction has laid a certain foundation for image processing. However, due to limited time and level, there are still some shortcomings in this research. When the image is acquired by the camera, there will be certain errors in the image parameters, resulting in linear distortion of the image during imaging. Therefore, in future research, taking linear distortion into account, the imaging error will be shortened, thereby improving social media blur, the precision of interactive 3D reconstruction of static images.

Conflict of interest: Authors state no conflict of interest.

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