Depth measurement using single camera with fixed camera parameters

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Abstract: Owing to the space limitation and the strict requirement on operation, depth measurement using single visual sensor is necessary in many applications, such as mini-robot, precision processing and micro/nano-manipulation. Depth from defocus (DFD), a typical method applied in depth reconstruction, has been extensively researched and has developed greatly in recent years. However, all the existing DFD algorithms has focused only on the situation that blurring images with different camera parameters (i.e. focal length or radius of the lens), and it resulted in the inapplicability of these algorithms in cases where any change of camera parameters is absolutely forbidden. Therefore a novel DFD method considering different images with fixed camera parameters is given. First, the blurring imaging model is constructed with the relative blurring and the diffusion equation. Secondly the relation between depth and blurring is discussed. Subsequently, the depth measurement problem is transformed into an optimisation issue. Finally, simulations and experiments are conducted to show the feasibility and effectiveness of the proposed method.

1 Introduction

Depth measurement, that is, methods to attain 3D information from 2D images, is an important research field in computer vision, and now it has been one of the key techniques in many fields, such as medicine, robotics, remote-sensing and micro/nano-manipulation. In recent years, there are various 3D reconstruction methods, including volumetric methods, depth from stereo (DFS), depth from focus (DFF) and depth from defocus (DFD) [1], researched and used in real applications.

Volumetric methods usually reconstruct 3D models of external anatomical structures from 2D images. They represent the final volume using a finite set of 3D geometric primitives. Then, from an image sequence acquired around the object to reconstruct, the images are calibrated and the 3D models of the referred object are built using different approaches of volumetric methods. These methods work in the object volumetric space and do not require a matching process between the images used. Thus, typically, the 3D models are built from a sequence of images, acquired using a turntable device and an off-the-shelf camera [2, 3]. However, in some real applications, we do not need to reconstruct the 3D model of objects, because depth is enough to understand the 3D relationship of scenes.

DFD estimates depth from two images of the same scene captured by cameras at different positions and with different postures [4]. Since it has to extract and match feature points in these images, the computational task is so huge. As for DFF, it uses a mapping relation between focus and depth to estimate depth. It obtains a sequence of images with different depths, measures the focus degree using a measurement operator [5, 6] and attains the desired depth when the measurement value is maximal or minimal. Compared to DFS, DFF is simple in principle, but its estimation accuracy is highly related to the number of images.

DFD is first introduced by Pentland in 1987 [7]. It has been proved to be an effective depth reconstruction method by using the concept of blurring degree of region images with limited depth of field [8–10]. Usually, DFD algorithm captures two images obtained with different camera parameters, measures blurring degree at every point and estimates depth using the point spread function. During the past years, DFD has become attractive because (i) it requires only two images; (ii) it avoids matching and masking problems and (iii) it is effective both in the frequency domain and in the spatial domain [11, 12].

All the existing DFD algorithms can be divided into two kinds: local DFD algorithm and global DFD algorithm. In local DFD, a window around every pixel point is predefined, and the point’s blurring is defined as that of the window [7, 13]. However, the difficulty in selecting proper size of window is a well-known disadvantage of DFD algorithm, because there is a trade-off between having a window that is as large as possible to average out noise, but as small as possible to guarantee that within it [14, 15]. As far as global DFD is concerned, its main idea is completely different from the local DFD algorithm, since it works on the entire image without information of its radiance, or the appearance of the surfaces, and depth. Therefore it is
necessary to construct the depth model and the radiance model simultaneously [14, 16–18]. This, however, will bring the problem of huge computation cost. A general method to solve this problem is to simplify the imaging model, for example, assuming the scene contains ‘sharp edges’, that is, there are discontinuities in the scene [19]. Another way is to use a cubic function or structure light to approach the radiance [20, 21]. Unfortunately, both local DFD and global DFD are on the basis of attaining two defocused images with different camera parameters which may destroy the camera drastically if the camera’s amplification level is high.

In this paper a novel global DFD method is proposed. The blurring imaging model is constructed with the relative blurring and the diffusion equation, and the relation between depth and blurring is discussed. Since the proposed method needs only one camera with fixed camera parameters, the process is simple. The simulation and experimental results show that it can attain depth with high precision.

The contents of this paper are organised as follows. First, in Section 2, the imaging model and the diffusion equation are proposed. Secondly, the relative blurring and the novel DFD method are introduced in Sections 3 and 4, respectively. Subsequently, in Section 5, the simulation and experimental results based on the new method are given. Finally, Section 6 is the conclusion of this paper.

2 Imaging model for defocus

2.1 Imaging theory for defocus

Based on the standard optical theory, when \( f \) (focal length), \( u \) (distance of the object from the principal) and \( v \) (distance of the focused image from len’s plane) satisfy (1), the interested image is focused, that means, the image at the source point is a focused point, as shown in Fig. 1.

\[
\frac{1}{u} + \frac{1}{v} = \frac{1}{f} \tag{1}
\]

If (1) is not satisfied, the focused point will become a blurring circle, and its distribution can be denoted as a 2D Gaussian function, called the point spread function

\[
h(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{2}
\]

where \( x \) and \( y \) are the horizontal and the vertical axis, respectively; \( \sigma \) denotes the spread of the Gaussian kernel.

Therefore a blurring image can be theoretically considered as the summation of some blurring points, and this process can be denoted by the following convolution function

\[
E(x, y) = I(x, y) * h(x, y) \tag{3}
\]

where \( E(x, y) \) and \( I(x, y) \) are the blurring image and the focused image, respectively, and the radius of the blurring round satisfies

\[
b = \frac{Dv}{2}\left|\frac{1}{f} - \frac{1}{v} - \frac{1}{s}\right| \tag{4}
\]

where \( s \) denotes depth of the blurring point and \( D \) denotes the radius of the lens.

2.2 Imaging model denoted by the diffusion function

Suppose the point spread function is not shift-invariant, that is, (2) can be rewritten as follows

\[
h(\sqrt{x^2 + y^2}) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{5}
\]

Then (3) can be denoted as an isotropic diffusion equation

\[
\begin{cases}
\dot{u}(x, y, t) = a\Delta u(x, y, t) & a \in [0, \infty) \quad t \in (0, \infty) \\
u(x, y, 0) = r(x, y)
\end{cases} \tag{6}
\]

Consider \( u(x, y, 0) \) to be a focused image. The solution of the diffusion equation can be obtained in terms of convolution of the image with a temporally evolving Gaussian kernel, so the diffusion equation can be introduced into the process of the defocus imaging, where \( a \) is called the diffusion coefficient, \( \Delta = (\partial^2/\partial t^2) \) and ‘\( \Delta \)’ denotes the Laplacian operator.

\[
\Delta u = \frac{\partial^2 u(x, y, t)}{\partial x^2} + \frac{\partial^2 u(x, y, t)}{\partial y^2} \tag{7}
\]

If the depth map is an equifocal plane, then \( a \) is constant or \( a \) is shift-variant. It is also easy to verify that the variance \( \sigma \) is related to the diffusion coefficient \( a \) via

\[
\sigma^2 = 2ta \tag{8}
\]

On the other hand, if the depth map is not an equifocal plane, the diffusion equation is as follows

\[
\begin{cases}
\dot{u}(x, y, t) = \nabla \cdot (a(x, y)\nabla u(x, y, t)) & t \in (0, \infty) \\
u(x, y, 0) = r(x, y)
\end{cases} \tag{9}
\]

where ‘\( \nabla \)’ denotes the gradient operator and ‘\( \nabla \)’ is the divergence operator

\[
\nabla = \left[\begin{array}{c}
\frac{\partial}{\partial x} \\
\frac{\partial}{\partial y}
\end{array}\right]^T, \quad \nabla \cdot = \frac{\partial}{\partial x} + \frac{\partial}{\partial y} \tag{10}
\]
3 Relative blurring

From (6) and (9), we can see that the radiance \( r(x, y) \) is required in order to construct the diffusion equation. However, in some situations, attaining the radiance is too complicated to be realised. Moreover, the resolution is always very low without knowing the accurate restoration model. Therefore a concept of relative blurring is introduced by Favaro [22].

Suppose there are two images \( E_1(x, y) \) and \( E_2(x, y) \) for two different focus settings. Also, \( \sigma_1 < \sigma_2 \) (i.e. \( E_1 \) is more defocused than \( E_2 \)), then \( E_2 \) can be written as

\[
E_2(x, y) = \int \frac{1}{2\pi\sigma_2^2} \exp\left(-\frac{(x-u)^2+(y-v)^2}{2\sigma_2^2}\right) r(u, v) \, du \, dv
\]

\[
\times \int \frac{1}{2\pi\sigma_1^2} \exp\left(-\frac{(u-\bar{u})^2+(v-\bar{v})^2}{2\sigma_1^2}\right) r(\bar{u}, \bar{v}) \, d\bar{u} \, d\bar{v}
\]

\[
= \int \frac{1}{2\pi\Delta\sigma^2} \exp\left(-\frac{(x-u)^2+(y-v)^2}{2\Delta\sigma^2}\right) E_1(u, v) \, du \, dv
\]

(11)

where \( \Delta\sigma^2 \equiv \sigma_2^2 - \sigma_1^2 \) is called the relative blurring. Thus, (11) can be explained as the solution of (6), but the initial value is \( E_1 \), rather than \( r \). So, (6) can be written as

\[
\begin{aligned}
\dot{u}(x, y, t) &= a\Delta u(x, y, t) \quad a \in [0, \infty) \quad t \in (0, \infty) \\
\dot{u}(x, y, t_i) &= E_i(x, y)
\end{aligned}
\]

(12)

Suppose \( t_i = 0 \), then

\[
\begin{aligned}
\dot{u}(x, y, t) &= a\Delta u(x, y, t) \quad a \in [0, \infty) \quad t \in (0, \infty) \\
\dot{u}(x, y, 0) &= E_1(x, y)
\end{aligned}
\]

(13)

Equation (9) becomes

\[
\begin{aligned}
\dot{u}(x, y, t) &= \nabla \cdot (a(x, y)\nabla u(x, y, t)) \quad t \in (0, \infty) \\
\dot{u}(x, y, 0) &= E_1(x, y)
\end{aligned}
\]

(14)

When the time-shifted is \( \Delta t \), the solution of the diffusion equation is \( u(x, y, \Delta t) = E_2(x, y) \), and \( \Delta t \) can be defined as

\[
\Delta\sigma^2 = 2(t_2 - t_1)a \equiv 2\Delta ta
\]

(15)

Thus, the relation between the relative blurring and the depth map can be denoted as

\[
\Delta\sigma^2 = \gamma^2(b_2^2 - b_1^2)
\]

(16)

where \( \gamma \) is a constant between the blurring radius and the blurring degree, \( b_i \) (\( i = 1, 2 \)) (see (4)) is a function of the depth map.

4 Method

As mentioned above, in DFD algorithm, two defocused images for different camera parameters are required, and the normal method to capture them is to change \( f, v \) or \( D \). However, it is difficult to realise in some situations, such as in micro/nano-manipulation where microscopes with high magnification are used. For this reason, a new DFD with changed depth is proposed in this section.

4.1 DFD with unknown variation value of depth

Suppose \( E_1(x, y) \), whose depth map is \( s_1(x, y) \), is the defocused image attained before variation, and \( E_2(x, y) \) is another defocused image attained after variation. In this section, we will propose a new DFD method in which the depth map \( s_2(x, y) \) is attained through a depth change \( \Delta s \), and the theory is shown in Fig. 2.

\[
s_1(x, y) - s_2(x, y) = \Delta s(x, y)
\]

(17)

Based on (14), the following functions can be given by

\[
\begin{aligned}
\dot{u}(x, y, t) &= \nabla \cdot (a(x, y)\nabla u(x, y, t)) \quad t \in (0, \infty) \\
u(x, y, 0) &= E_1(x, y) \\
u(x, y, \Delta t) &= E_2(x, y)
\end{aligned}
\]

(18)

where the relative blurring can be denoted as

\[
\Delta\sigma^2(x, y) = \gamma^2(b_2^2(x, y) - b_1^2(x, y))
\]

\[
= \frac{\gamma^2D^2\nu^2}{4} \left[ \frac{1}{v - 1} \cdot \frac{1}{s_2(x, y)} \right]^2 - \frac{1}{v - 1} \cdot \frac{1}{s_1(x, y)} \right)^2
\]

(19)

From (15), the diffusion coefficient can be denoted as

\[
a(x, y) = \frac{\gamma^2D^2\nu^2}{8\Delta t} \left[ \left( \frac{1}{v - 1} \cdot \frac{1}{s_2(x, y)} \right)^2 - \left( \frac{1}{v - 1} \cdot \frac{1}{s_1(x, y)} \right)^2 \right]
\]

(20)

Thus, the desired depth map is

\[
s_2(x, y) = 1 \left\{ \frac{1}{v - 1} \pm \sqrt{\left[ \frac{1}{v - 1} \right]^2 - \frac{1}{v} \cdot \frac{1}{s_2(x, y)} \right. \right. \\
\left. \left. - \frac{1}{s_1(x, y)} \right) \right\} \frac{8\Delta ta(x, y)\nu}{\gamma^2D^2\nu^2}
\]

(21)

As a global algorithm, we construct the following optimisation problem to calculate the solutions of the
diffusion equation

\[ \hat{s} = \arg \min_{s_1, \cdots, s_k} \int \int (u(x, y, \Delta t) - E_2(x, y))^2 \, dx \, dy \]  
\[ \text{(22)} \]

However, the optimisation process above is ill-posed [21], that is, the minimum may not exist, and even if it exists, it may not be stable with respect to data noise. A common way to regularise the problem is to add a Tikhonov Penalty

\[ \hat{s} = \arg \min_{s_1, \cdots, s_k} \int \int (u(x, y, \Delta t) - E_2(x, y))^2 \, dx \, dy \]
\[ + \alpha \| \nabla s_1(x, y) \|^2 + \alpha k \| s_2(x, y) \|^2 \]  
\[ \text{(23)} \]

where the additional term imposes a smoothness constraint on the depth map. In practice, we use \( \alpha > 0 \), \( k > 0 \) which are all very small, because this term has no practical influence on the cost energy denoted as

\[ F(s) = \int \int (u(x, y, \Delta t) - E_2(x, y))^2 \, dx \, dy + \alpha \| \nabla s \|^2 + \alpha k \| s \|^2 \]  
\[ \text{(24)} \]

Thus, the solution process is equal to the following

\[ \hat{s} = \arg \min_{s} F(s) \]
\[ \text{s.t. Eq. (18) and Eq. (21)} \]  
\[ \text{(25)} \]

Equation (25) is a dynamic optimisation which can be solved by the gradient algorithm. The algorithm can be divided into following steps (the detailed process can be seen in the literature [22]):

1. Give camera parameters \( f, D, \gamma, v, s_0 \); two defocused images \( E_1, E_2 \); a threshold \( \epsilon \); \( \alpha \) and optimisation step \( \beta \);
2. Initialise the depth map with a plan \( s \). \( T \) be simple, we can suppose that the initial plane is an equifocal plane;
3. Compute (19) and obtain the value of the relative blurring;
4. Compute (18) and obtain the solution \( u(x, y, \Delta t) \) of diffusion equation;
5. Compute (30) with the solution of Step (4). If the cost energy is below \( \epsilon \), stop; or compute the following equation with step \( \beta \)

\[ \frac{\partial s}{\partial t} = -F'(s) \]  
\[ \text{(26)} \]

6. Compute (21). Update the depth map, and return to Step (3).

With a camera whose parameters are fixed, the method can be used to reconstruct depth information although the variation depth value is not known. So, if the initial depth is known, the dynamic depth, as well as the dynamics equation or kinematics equation, can be constructed.

4.2 DFD with known variation value of depth

If the initial depth of a defocused image is not known, we can also attain it through changing a depth. Suppose \( E_1(x, y) \), whose depth \( s_1(x, y) \) is unknown, is the defocused image attained before variation, and \( E_2(x, y) \), whose depth map \( s_2(x, y) \), is another defocused image attained after variation, we can estimate the depth map \( s_1(x, y) \) through increasing or decreasing depth \( \Delta s \) which is known. The theory is shown in Fig. 2.

Suppose \( s_0 \) is the focused depth

\[ \frac{1}{f} - \frac{1}{v} = \frac{1}{s_0} \]  
\[ \text{(27)} \]

Based on (4), the blurring radius \( b \) is

\[ b = \frac{Dv}{2} \left[ \frac{1}{f} - \frac{1}{v} \right] - \frac{1}{s_0} = \frac{Dv}{2} \left[ \frac{1}{s_0} - \frac{1}{s_0 + ds} \right] \]  
\[ \text{(28)} \]

where \( ds = |s - s_0| \). According to (16), we have

\[ -2\Delta s \cdot s_1^2 + (2\Delta s^2 - 2\Delta s \cdot s_0) \cdot s_1 + 2\Delta s^2 \cdot s_0 = \frac{4\Delta s^2}{\sqrt{f^2D^2v^2}} \]  
\[ \text{(29)} \]

Equation (29) can be changed into the following form

\[ as^4 + bs^3 + cs^2 + ds + e = 0 \]  
\[ \text{(30)} \]

where

\[ a = \frac{4\Delta s^2}{\sqrt{f^2D^2v^2}} s_0, \quad b = -\frac{8\Delta s^2}{\sqrt{f^2D^2v^2}} s_0 \cdot \Delta s \]
\[ c = \frac{4\Delta s^2}{\sqrt{f^2D^2v^2}} s_0 \cdot \Delta s^2 + 2\Delta s, \quad d = 2\Delta s(s_0 - \Delta s) \]
\[ e = -\Delta s^2 \cdot s_0 \]

The solution process is as follows:

1. Normalise the coefficients

\[ a = 1, \quad b = b/a, \quad c = c/a, \quad d = d/a, \quad e = e/a \]

2. Transform the quartic equation into a cubic equation

\[ y^3 + ky^2 + my + n = 0 \]  
\[ \text{(31)} \]

where \( k = -c, m = bd - 4c, n = -d^2 - b^2e + 4ce \).

The solution of (31) is

\[ y = \frac{1}{3} \sqrt[3]{(2k^3/27) - (k^2/3) + n} - \frac{z}{2} + \frac{1}{3} \sqrt{1 - \frac{4}{27}(2k^3/27 - (k^2/3) + n)^2 + \frac{z^3}{3}} \]  
\[ \text{(32)} \]

where

\[ z = \sqrt[3]{\left(\frac{(2k^3/27) - (k^2/3) + n)^2}{4} + \left(-\frac{(k^2/3) + m}{3}\right)^3 \right)} \]
3. Compute the desired depth map

\[
\begin{aligned}
  s = & \frac{-\left(\frac{1}{2}b + \bar{s}\right) \pm \sqrt{\left(\frac{1}{2}b + \bar{s}\right)^2 - 4\left(\frac{1}{2}v + \bar{s}\right)}}{2} \\
  s = & \frac{-\left(\frac{1}{2}b - \bar{s}\right) \pm \sqrt{\left(\frac{1}{2}b - \bar{s}\right)^2 - 4\left(\frac{1}{2}v - \bar{s}\right)}}{2}
\end{aligned}
\] (33)

where

\[
\bar{s} = \sqrt{\frac{1}{4}b^2 - c + y}; \quad \bar{s} = \sqrt{\frac{1}{4}y^2 - c}
\]

The steps are the same as that in Section 4.1 except that (21) is replaced by (33).

When the observing camera is fixed, the method can be used to reconstruct depth information after the depth changing a known distance although the initial depth is unknown.

5 Simulation and experimental results

In order to validate the new proposed algorithm, we used a number of synthetic images and two nano-standard grid images to test it. In the simulation, some basic parameters are as follows: \(f = 12\) mm, \(v = 12.2\) mm, \(s_0 = 850\) mm, \(F = 2\), \(D = f/2\), \(\gamma = 0.002\). The effect of the proposed algorithm was tested by using, respectively, a smooth plane, a slope plane, a cosine plane and a wave plane. Furthermore, in order to investigate the influence of the texture sharpness on the algorithm, we added three levels of texture sharpness along the horizontal axis. Finally, the error maps in each experiment were constructed and the mean square errors of the proposed method in the cosine plane and slope were computed to test the precision of this algorithm. In real experiment, we tested our algorithm to reconstruct the depth information of a nano-standard grid, in which every small grid is 500 nm high and 1500 nm wide. We used the microscope HIROX-7700 and magnified the grid 7000 times, and the rest of the parameters are \(f = 0.357\) mm, \(s_0 = 3.4\) mm, \(F\)-number = 2, \(D = f/2\).

Fig. 3 Two defocused images in a cosine plane

(a) Image before depth variation
(b) Image after depth variation

Fig. 4 Depth image in grey scale

(a) Calculated depth image in a cosine plane
(b) True depth image in a cosine plane
5.1 Simulation with unknown variation value of depth

First, the simulations using algorithm in Section 4 were conducted. The results are shown in Figs. 3–9.

Figs. 3–5 are the simulation results in a cosine plane, where Fig. 3a is the defocused image before depth variation and Fig. 3b is the defocused image after depth variation; Fig. 4a is the computed depth map with our algorithm and Fig. 4b is the true depth map; Fig. 5a is the computed map with our algorithm and Fig. 5b is the true map.

From Fig. 3, we can see that the defocused image after depth variation is more defocused than the image before variation, so we can conclude that the direction of the variation is the direction opposite to the ideal depth. From Figs. 4 and 5, we can see that the calculated depth is very close to the true depth and it is hard to see the difference between them. Besides, the algorithm is not influenced by the texture sharpness.

Figs. 6–8 are the simulation results of a slope, where Fig. 6a is the defocused image before depth variation and Fig. 6b is the defocused image after depth variation; Fig. 7a is the computed depth map with our algorithm and Fig. 7b is the true depth map; Fig. 8a is the computed map with our algorithm and Fig. 8b is the true map.

From these figures, the following two aspects can be concluded: (i) the new algorithm can attain good results in construction depth map for different scenes; (ii) the
influence of the texture sharpness on the proposed algorithm is very little.

In order to investigate the precision of the new algorithm, we constructed the error map $\phi$ between the true depth $s$ and the estimated depth $\tilde{s}$ with the cosine image, and computed the mean square error $\varphi$ of the whole image. The computed formulas are shown in (34) and (35).

$$\phi = \frac{\tilde{s}}{s} - 1$$  \hspace{1cm} (34)

$$\varphi = \sqrt{E[(\frac{\tilde{s}}{s} - 1)^2]}$$  \hspace{1cm} (35)

The result map is shown in Fig. 9. From the result, it can be seen that the precision of the proposed method is very high when the variation value of depth is unknown, the mean square error of the whole image is equal to 0.0094 and the maximal error is less than 0.5%.

5.2 Simulation with known variation value of depth

In this sub-section, we tested the proposed algorithm with known variation, and the results are shown in Figs. 10–16. Figs. 10–12 are the simulation results in a wave plane,
Fig. 10  Two defocused images in a wave plane
   a  Image before depth variation
   b  Image after depth variation

Fig. 11  Depth image in grey scale
   a  Calculated depth image in a wave plane
   b  True depth image in a wave plane

Fig. 12  Depth image of curve
   a  Calculated depth image in a wave plane
   b  True depth image in a wave plane
**Fig. 13** Two defocused images in a smooth plane

a Image before depth variation  
b Image after depth variation

**Fig. 14** Depth image in grey scale

a Calculated depth image in a smooth plane  
b True depth image in a smooth plane

**Fig. 15** Depth image of curve

a Calculated depth image in a smooth plane  
b True depth image in a smooth plane
Figs. 13–15 are the simulation results in a smooth plane and Fig. 16 is the error map of a slope image, in which the mean square error of the whole image is equal to 0.0026 and the maximal error is less than 0.4%. From these results, we can see that the error of our reconstruction algorithm is slightly larger at the edge of the image and smaller at other regions. This kind of phenomenon results from the gradually advancing process of the optimisation method. However, with very low error it can certainly satisfy the high precision requirement of micro/nano-manipulation.

5.3 Real experiment

In real experiment, the grid whose size is 120 × 50 pixels was conducted. The results are shown in Figs. 17–21. Fig. 17a is the defocused image before depth variation, and Fig. 17b is the defocused image after depth variation; the computed depth map in grey scale shown in Figs. 18 and 19 is the reconstructed depth of the nano-grid. In order to investigate the precision of the new algorithm, we also constructed the error image between the true depth \( s \) and the reconstructed depth \( \tilde{s} \), and computed the mean square error of the whole

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**Fig. 16** Error map in a smooth plane

**Fig. 17** Two defocused images of the nano-grid

a Image before depth variation

b Image after depth variation

**Fig. 18** Depth map in grey scale

**Fig. 19** Calculated depth of the grid

**Fig. 20** True depth of the grid

**Fig. 21** Error depth of the grid
image. Fig. 20 is the true depth of the grid and Fig. 21 is the error depth.

From the experiment, we can see that the new algorithm is effective to reconstruct the depth of the nano-grid and the precision of the proposed method is very high. The mean square error is equal to 0 and the average error is 10.4 nm.

From the results of the simulations and the real experiment, we can see that the proposed algorithm is not only effective to reconstruct the depth information with synthetic images, but also can reconstruct the depth information with real images. The average error is only about 2.3% and it can certainly satisfy the high precision requirement of micro/nano-manipulation.

6 Conclusion

In this paper, depth measurement problem using single camera with fixed camera parameters is researched based on an improved global DFD method. Our primary contribution is (a) to estimate the depth map with unknown variation value of depth and (b) to obtain the depth map with known variation value of depth, if the new global DFD algorithm is used at two different situations. Therefore the new algorithm can be used to attain 3D information in one-eye vision, hand–eye system, especially in micro/nano-manipulation. Extensive simulations and real experiments are performed with a number of synthetic images. The results show that the proposed algorithm is an effective method to measure depth using defocused images without changing camera parameters.

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