A Novel Method for Shape From Focus in Microscopy Using Bezier Surface Approximation

MANNAN SAEED MUHAMMAD AND TAE-SUN CHOI*
Signal and Image Processing Laboratory, School of Information and Mechatronics, Gwangju Institute of Science and Technology, Gwangju, South Korea

KEY WORDS 3D shape reconstruction; shape-from-focus; depth estimation; focus measure; Bezier surface; pixel intensities; microscopy

ABSTRACT In this article, we introduce a novel shape from focus method to compute 3D shape of microscopic objects, based on modified-pixel intensities and Bezier surface approximations. A new and simple but effective focus measure is proposed. In our focus measure, the original intensities of a sequence of small neighborhood are modified by subtracting the maximum of the values of first and last frames. An initial depth map is calculated by finding the maximum of the pixel’s focused energy and its corresponding frame number. Missing information between two consecutive frames, false depth detection, and enhancement of noise related intensities may provide inaccurate depth map. To overcome these problems and to produce an accurate depth map, we proposed Bezier surface approximation. The proposed method is tested using synthetic and real image sequences. The comparative analysis demonstrates the effectiveness of the proposed method. Microsc. Res. Tech. 73:140–151, 2010. © 2009 Wiley-Liss, Inc.

INTRODUCTION

There are two main categories of recovering 3D shape of an object, namely, active methods and passive methods. In active methods, sonar, laser range finders and many more like them are included. Whereas, passive methods include shape from shading, shape from motion (motion parallax), stereo vision, shape from defocus, and shape from focus (SFF). In microscopy, active methods being expensive are sometimes impractical to use. Whereas, passive methods are more popular because of being cheaper, and they are easy to implement. Particularly, SFF has many advantages over other passive methods such as stereo and motion parallax as they encounter the correspondence problem. Therefore, image focus analysis has been extensively studied in auto-focusing and 3D shape recovery in microscopy (Geusebroek et al., 2000; Mahmood et al., 2008; Shim et al., 2009; Sun et al., 2004; Xie et al., 2007). However, accuracy of SFF methods need to be further improved for better 3D shape.

In SFF methods, a stack of images are acquired by a single camera at different focus levels. The first step is to compute the focus quality of each pixel of every frame by applying a focus measure operator, and then the depth map is computed by maximizing the focus value along the optical axis. Focus measure is defined as a quantity for locally evaluating the sharpness of a pixel. In literature, many focus measures have been reported in spatial as well as in transform domains (Helmli and Scherer, 2001; Subbarao et al., 1992; Sun et al., 2004). Laplacian, modified Laplacian (ML), sum of modified Laplacian (SML), Tenenbaum (TEN) focus measure, gray-level variance (GLV), and $M_2$ focus measure are the famous among them. The Laplacian operator, being a point and symmetric operator, is the commonly used focus measure. The focus value of an image is obtained by adding second derivatives in the $x$- and $y$-directions. In the case of textured images, the $x$ and $y$ components of the Laplacian operator may cancel out and subsequently yield no response. Therefore, Laplacian is modified by ML that can be computed by adding the squared second derivatives of $x$ and $y$ components. To improve the robustness for weak-textured images, Nayar and Nakagawa (1994) presented SML. It is computed by summing ML values in a local window. TEN is gradient magnitude maximization method that measures the sum of the squared responses of the horizontal and vertical Sobel masks. For robustness, resultant values are summed in a local window for each pixel in the focus volume. One of the other well-known focus measure is the GLV. It is based on the idea that in the case of a sharp image, the variance of the intensities is higher than that for a blurred image. Xiong and Shafer (1993) reported $M_2$ focus measure, which is actually modified version of TEN focus measure. The ratio of energies of high-frequency components to low-frequency components in discrete wavelet transform is also a good focus quality measure (Xie et al., 2007).

The discreteness of shape into the frames of images results in loss of information in between the two consecutive frames. As a result, the optimum depth value for some pixels is difficult to calculate accurately. Hence, to address this issue among others, approximation techniques have been applied to the results of the focus measures to construct a more accurate depth.

*Correspondence to: Tae-Sun Choi, Signal and Image Processing Lab, School of Information and Mechatronics, Gwangju Institute of Science and Technology, Gwangju 500712, South Korea. E-mail: tschoi@gist.ac.kr

© 2009 WILEY-LISS, INC.
map. Nayar and Nakagawa (1994) proposed SFF.TR based on Gaussian interpolation. For each object point, three focus values near the peak are fitted to Gaussian model, and the position of the mean is taken as optimal depth. They applied SML to find the initial peak and focused a best focused point. Mahmood et al. (1993) introduced the concept referred to as focused image surface (FIS) and proposed a method SFF.FIS to recover the shape of an object. The FIS of an object is defined as the surface formed by the set of points at which the object points are focused by a camera lens. The initial estimate is obtained by SML, and it is then refined by searching for a planar surface that maximizes the focus measure computed over pixels on FIS. Choi and Yun (2000) proposed the approximation of FIS by a piecewise curved surface rather than through the use of a piecewise planar approximation, where it was estimated by interpolation using a second-order Lagrange polynomial. Asif et al. (2001) used neural networks on GLV results to learn the shape of FIS by optimizing the focus measure over a small 3D window. Furthermore, Ahmad and Choi (2005a,b) proposed the method SFF.DP using dynamic programming (DP) for handling the computational complexity of FIS. In first step, SML is applied to compute the initial depth map. The whole 3D focus volume is then segmented into slices along x-axis and y-axis, and the optimal depth is then computed by applying heuristic model. Noguchi and Nayar (1994), and Malik and Choi (2004) studied the effects of light on the recovery of 3D shape. Mahmood et al. (2008) suggested SFF.PCA by employing principal component analysis (PCA) in discrete cosine transform (DCT) domain to recover the 3D shape of an object. In most of these methods, initial depth map is generated through gradient-based methods (like SML), which is generally prone to noise, and it is propagated in approximation step resulting in an inaccurate depth map.

In this article, we introduce a novel SFF method. A new, simple, and effective focus measure is proposed to find the best focused points. At first, we modify the values of pixels in the neighborhood stack by taking difference of original and the maximum of the values of first and last frames. The initial depth is then computed by finding the frame number that maximizes the focus value in the modified intensity vector. We propose Bezier surface (BS) to approximate 3D shape of the object from its initial estimate. It not only provides accurate depth map but also helps to suppress noise caused by false detection of depth by focus measure in the first step. Experimental results and comparative analysis demonstrate the effectiveness of the proposed approach.

This article is organized in the following way. In the first section, some details of related work are given from the literature. Then, the proposed focus measure and the proposed method are illustrated in detail. In later section, the results are presented and compared with existing approaches. The final section concludes the study.

**MATERIALS AND METHODS**

**Image Acquisition System**

For experiments, we have used three different objects; simulated cone, coin and liquid crystal display (LCD) filter. The simulated cone is the synthetic object and its images are generated by computer simulations. The details of simulated cone images are given by Subbarao and Choi (1995), and we have used the same image sequence. The coin images are the magnified images of Lincoln’s head at the back of one-cent coin (US). The LCD-filter images are microscopic images of LCD-color filter, and these images are obtained by microscopic control system (MCS). The system consists of a personal computer integrated with frame grabber board (Matrox Meteor-II) with a CCD camera (SAMSUNG CAMERA SCC-341) mounted on a microscope (NIKON OPTIPHOT-100S). Software in the computer acquires images by controlling the lens position through a stepper-motor driver (MAC 5000) having a minimum of 2.5-nm step length. All the images are taken by varying the object plane by step size \(D_{\text{Do}}\) and are stored in a sequence on every step, such that: (i) the object moves toward (or away from) the lens assuring that the complete object is first defocused then gradually it focuses (on a part of the object), and then it is again completely defocused; (ii) we assume, there is no magnification when the images are taken (Muhammad et al., 2008). The sequences of the two microscopic objects, LCD-filter and the coin, consist of 60 and 68 images, and they were obtained under 500× magnification using 2,500 steps and 100× magnifications with 12,500 steps, respectively. Figure 1 shows frames first to last of the simulated cone. The images show that the simulated cone follows the aforementioned statements (i and ii). Figure 2 shows the 10th image in the image stack for coin and LCD-filter.

**Problem Formulation**

In SFF methods a sequence of images are used, taken by a single camera at different focus levels, to compute the depth of the object in the scene. Then, the entire image sequence is searched to find the best focused image frame for a particular point in the image.
space. By setting the camera parameters for that image frame, the distance of the corresponding object point is computed by using the Lens-Formula [Eq. (1)]. Where \( f \) is the focal length, \( D_o \) and \( D_i \) are the object and image distances from the lens, respectively. Since, this method involved focusing the object for finding 3D shape, therefore, it is called SFF.

\[
\frac{1}{f} = \frac{1}{D_o} + \frac{1}{D_i}
\]  

(1)

In well-focused (gray scale) image, the values of the pixels (white and black) have relatively greater difference than that in an ill-focused (gray scale) image. The equation for the blur radius \( R \) caused by the focusing of the object surface is given by the Eq. (2).

\[
R = \frac{D}{2} \left( \frac{1}{f} - \frac{1}{D_o} - \frac{1}{D_i} \right)
\]  

(2)

where \( D \) is the diameter for the lens aperture, and \( s \) is the distance for the image sensor plane from the lens as shown in Figure 3.

Using the thin-lens-model stated above, when the point \( P \) on the object is best focused in the focused plane, its corresponding pixel intensity value in the image is its true value (i.e., in a gray-scale image, for white-object points on the body the pixel intensity value in the image will be near to maximum and for the black-object points the pixel intensity value will be near to minimum), whereas, when the point is defocused it will have the defused value (i.e., between white and black). This is explained by Figure 4.

**Motivation**

As discussed in previous section, white-object points are well focused at maximum gray levels, whereas, black object points are well focused at minimum gray levels. This phenomenon motivated us to propose a new focus measure that modifies the pixel values in the image stack, so that the two problems of finding
maxima or minima of focus curve are changed into a single problem of finding maxima only. The proposed focus measure is faster, simple to compute and more precise than previous focus measures. In conventional SFF methods, depth values for each object point are computed by maximizing focus values along the optical axis. However, missing information between two consecutive frames results in producing an inaccurate depth map. In literature, interpolation techniques were employed to overcome this problem. These methods interpolate focus values by fitting them to some specific model such as Gaussian. In reality, the distribution of focus values may not follow the Gaussian model, so these techniques fail to estimate accurate depth. We suggest the use of BS to approximate 3D shape, so these techniques fail to estimate accurate depth. However, missing information between two frames results in producing an inaccurate depth map. In literature, interpolation techniques were employed to overcome this problem. These methods interpolate focus values by fitting them to some specific model such as Gaussian. In reality, the distribution of focus values may not follow the Gaussian model, so these techniques fail to estimate accurate depth. We suggest the use of BS to approximate 3D shape, so these techniques fail to estimate accurate depth.

Proposed Focus Measure

An image sequence \( I_n(X,Y) \) of an object is acquired by displacing object along the optical axis. The sequence consists of \( n \) images and each image is of dimensions \( X \times Y \). For each object point, we take the gray-level value of the pixels in a vector \( (n \times 1) \), defined as \( i,j P \). We modified these values according to the following formula:

\[
[i,j m_k]_{nx1} = \left[ \left( i,j p_k - \max \{ i,j p_1, i,j p_n \} \right)^2 \right]_{nx1}
\]

for all \( 1 \leq k \leq n \) where \( i,j p_k \) is the \( k \)th value in the original pixel intensity vector \( i,j P \), \( i,j p_1 \), and \( i,j p_n \) are the first and last \( (n) \) values in the pixel intensity vector, \( i,j m_k \) is the \( k \)th value in the modified pixel intensity vector \( i,j M \), \( i \) and \( j \) are the \( x \) and \( y \) positions of the pixel in special domain. The step size \( \Delta \) can be computed by Eq. (4).

\[
\Delta = \frac{S}{n}
\]

where \( S \) is the total displacement of object plane, and \( n \) is the total number of images in the sequence. The modified pixel intensity vector is then added together with its neighborhood in a window of size \( \omega \times \omega \), given by Eq. (5).

\[
[i,j r_k]_{nx1} = \left[ \sum_{x,y} i,x,j,y m_k \right]_{nx1}
\]

where \( i,j r_k \) is the \( k \)th element in vector \( i,j R \). The modified intensity vector changes the two problems (of finding maximum and minimum of pixel intensity vector) into a single problem (of finding maximum value in the focus curve). For the depth of each pixel, the corresponding frame number of the maximum value in the vector \( i,j R \) is taken, given by the Eq. (6).

\[
d_{i,j} = \arg \max_{1 \leq k \leq n} \left\{ i,j r_k \right\}
\]

where \( d_{i,j} \) is the \((i,j)\)th element of the depth-map matrix \( \delta \).

The process is repeated for all the object points. Once all the elements of matrix \( \delta \) are calculated, the 3D shape is then approximated by using BS.

3D Shape Approximation

Bezier-surface approximations are superior to meshes of triangles as a representation of smooth surfaces, since they are much more compact, easier to manipulate, and have much better continuity properties. In addition, other common parametric surfaces such as semispheres and cylinders can be well approximated by relatively small numbers of cubic BSs.

A BS \( \delta(u,v) \) is defined by a two-dimensional set of control points, \( a_{\alpha \beta} \), where \( \alpha \) is in the range of 0 and \( g \), and \( \beta \) is in the range of 0 and \( h \), with \( g + 1 \) rows and \( h + 1 \) columns, defined by the Eq. (7).

\[
\delta(u,v) = \sum_{\alpha=0}^{g} \sum_{\beta=0}^{h} B_{\alpha \beta}(u) B_{h \beta}(v) a_{\alpha \beta}
\]

where \( B_{\alpha \beta}(u) \) and \( B_{h \beta}(v) \) are the \( \alpha \)th and \( \beta \)th Besizer basis functions in the \( u \) and \( v \) directions, respectively. The basis functions are defined by the following equations (8) and (9):

\[
B_{\alpha \beta}(u) = \frac{g!}{\alpha!(g-\alpha)!} u^\alpha (1-u)^{g-\alpha}
\]

\[
B_{h \beta}(v) = \frac{h!}{\beta!(h-\beta)!} v^\beta (1-v)^{h-\beta}
\]

Since \( B_{\alpha \beta}(u) \) and \( B_{h \beta}(v) \) are of degree “\( g \)” and degree “\( h \)” functions, therefore BS of degree \((g, h)\) will be obtained. As the polynomial parameters \( u \) and \( v \) are in the range of 0 and 1, hence, the BS maps the unit square to a rectangular surface patch. The properties of BS are:

- BS of degree \((g, h)\) has control points \((g + 1, h + 1)\).
- \( \delta(u,v) \) passes through the control points \((\delta_{\alpha \beta})\) at the four corners of the control net \( \delta_{0,0} \delta_{g,0} \delta_{0,h} \delta_{g,h} \).
- \( B_{\alpha \beta}(u) \) and \( B_{h \beta}(v) \) are nonnegative for all \( g, h, i, j \), and \( u, v \) in the range of \((0,1)\).
- The sum of all \( B_{\alpha \beta}(u) \) and \( B_{h \beta}(v) \) is 1 for all the values of \( u \) and \( v \).
- The BS \( \delta(u,v) \) lies in the convex hull defined by its control points.
- Affine invariance is applicable to BS.

The object point \((i,j)\) is selected along with its eight-neighbors, and these nine-points are taken as the
control points. The matrix-representation of BS as a Cartesian product of two curves obtained by 2nd degree Bernstein-polynomial is given by Eq. (10).

\[
\delta(u, v) = \begin{bmatrix} u^2 & u & 1 \\ -2 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix}
\]

\[
\times \begin{bmatrix} d_{i-1,j-1} & d_{i-1,j} & d_{i-1,j+1} \\ d_{i,j-1} & d_{i,j} & d_{i,j+1} \\ d_{i+1,j-1} & d_{i+1,j} & d_{i+1,j+1} \end{bmatrix} \begin{bmatrix} 1 & -2 & 1 \\ -2 & 2 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} u^2 \\ v \\ 1 \end{bmatrix}
\]

(10)

As the BS maps unit square to the surface patch, the middle point value of the BS formed by the above process is taken as the corrected depth value of the object point \((i,j)\) as given by (11).

\[
[d_{i,j}^{\text{NEW}}] = \left( \delta \left( \frac{1}{2}, \frac{1}{2} \right) \right)_{i,j}
\]

(11)

The algorithm is repeated for all the object points, and finally the Bezier-depth map is computed, which represents the 3D shape of the object.

RESULTS AND DISCUSSION
Performance Measures

To make valid evaluations and comparisons, effective metrics should be used. In our proposed SFF approach, we have also introduced a new focus measure. So, it is reasonable to evaluate the performance of proposed focus measure, and then to compare the performance of...
SFF methods in terms of quality of generated depth map. We used two metrics, resolution (RM) and accuracy (AM) matrices, for focus measure comparisons.

RM metric characterizes the distribution of profile of FM, and it also gives how well out-of-focus features are suppressed. The definition is to that adopted by Xie et al. (2007).

\[
RM = \sigma = \frac{1}{\| M \|} \sqrt{\sum_{z=1}^{n} (Z - Z_f)^2 M^2(z)}
\]  

(12)

where \( n \) is the total number of images in sequence, \( Z_f \) is the best focused frame number among the focus curve function \( M(z) \) and \( \| M \| \) is its Euclidian norm.

AM measures the distance between the best focus position and the maximum of the focus curve. Smaller the measure is, the more accurate the focus measure, (Sun et al., 2004)

\[
AM = | Z_{+e} - Z_{-e} | 
\]  

(13)

where “\( e \)” is the error tolerance and can be specified by a number.

An image quality metric can be derived as a measure of the perceived difference from a reference image. If no differences can be perceived, then the reproduced image is indistinguishable from the original, and the image quality is at its maximum. Same can be derived for 3D shape comparisons. Hundreds of metrics have been proposed to deal with both general and specific aspects of image quality; however, we have chosen some of them to show the effectiveness of our results.

Mean squared error (MSE) is one of the ways to quantify the amount by which an image differs from the original image. MSE measures the average of square of the “error,” and it is the second moment (about the origin) of the error. RMSE is the square-root of MSE (Ahmet and Fisher, 1995; Bovic, 2005), defined as follows:
\[ \text{RMSE} = \sqrt{\frac{1}{mn} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} [I(i, j) - I'(i, j)]^2} \]  

where \( m \) is the number of horizontal pixels in the image, \( n \) is the number of vertical pixels, \( I(i, j) \) is the original image, and \( I'(i, j) \) is the modified image.

Universal quality index (\( Q \)) (Wang and Bovik, 2002) is designed by modeling any image distortion as the combination of three factors, and it is defined as follows by (15):

\[ Q = \frac{\sigma_{xy}}{\sigma_x \sigma_y} \cdot \frac{2 \sigma_{xy}}{(x)^2 + (y)^2} \cdot \frac{2 \sigma_x \sigma_y}{\sigma_x^2 \sigma_y^2} \]  

where \( \bar{x} \) and \( \bar{y} \) are the mean of \( x \) and \( y \), and \( \sigma_x \), \( \sigma_y \), and \( \sigma_{xy} \) are variance and covariance of \( x \) and \( y \). The first component is the correlation coefficient between \( x \) and \( y \) and its dynamic range is \([-1, 1]\). Correlation (Cor.) (Ahmet and Fisher 1995; Rodgers and Nicewander, 1988) is a metric that indicates the strength and direction of a linear relationship between two images. In general, correlation refers to the departure of two images from independence. The second component, with a value range of \([0, 1]\) measures how close the mean luminance is between \( x \) and \( y \). The third component measures how similar the contrasts of the images are.

**Algorithm Analysis**

Considering two object points ((101,101) \( P_1 \), (110,110) \( P_2 \)) in the simulated cone image sequence, we computed pixel intensity vector by taking values in all the images for a fixed object point as shown in the Figure 5, along \( Z \)-axis. The figure shows the pixel intensity vector for the object points ((101,101) \( P_1 \), (110,110) \( P_2 \)) in the simulated cone image sequence. The original intensity vector of the first-object point, ((101,101) \( P_1 \) has the first and last values as 78 and 84 with minimum as 13 and 39. For second-
object point, the original intensity vector \((110,110)\) has first and last values as 85 and 82 with maximum as 154 and 42. When Eq. (3) is applied to these vectors we get modified intensity vectors. The modified intensity vectors \((101,101)\) and \((110,110)\) have first and last values as 36 and 0, and 0 and 9, respectively; with maximums as 5,041 at 40 and 4,761 at 42, as shown in Figure 6. It can also be seen from Figure 6 that the proposed FM modified the two problem of finding maxima and minima (of two types of object points) into one-sin-
gle problem of finding maxima, thus reducing the complexity of the whole image space. To compute final values for the depth-map, the modified intensity vector is added together with its eight neighbors using Eq. (5). The depth values were found by searching maxima of sum of modified intensity vector and its corresponding frame number, and were found to be 40 and 46, respectively.

Once, the depth for all the object points in the image sequence is found, the initial depth map is computed. Further, to refine initial depth map estimate, a set of 3×3 control points are selected (starting from one end of the depth map), and the BS defined by these control points is computed. The depth values of eight neighbors of the object points \((110,110)\) are \([43 \ 39 \ 40; 40 \ 40 \ 43]\) and \([46 \ 46 \ 43; 46 \ 46 \ 43]\). The initial depth values of object point \((110,110)\) along with its eight neighbors are shown in Figure 7. These nine points (object point with eight neighbors) are taken as control points for computing depth. The depth values obtained by the BS for the object points are \([40 \ 40 \ 40; 40 \ 39.94 \ 40.25; 40 \ 40.25 \ 43]\) and \([43 \ 43.75 \ 46; 43.75 \ 45.06 \ 46; 46 \ 46 \ 46]\). The corrected depth values of the object points \((110,110)\) (after applying the BS) is shown in the Figure 8. The depth value of the central point is selected as the corrected depth for that pixel, as shown in the Figure 7. We obtained the corrected depth values 45.06, which is more accurate. The process is repeated for all the points in the depth map.

The 3D shape of the simulated cone reconstructed by different methods is given in Figures 9–12. Figure 9 shows the original depth map of the simulated cone; Figure 10 shows the depth map obtained by BS approximation; Figures 11 and 12 show the depth map of simulated cone by SFF.DP and SFF.TR.
We have also computed the depth map for the coin, and LCD-filter image sequence. Figures 13–15 show the reconstruction of depth map of coin and Figures 16–18 show LCD-filter by proposed and traditional methods.

Comparative Analysis

We chose the most commonly used focus measures SML, GLV, TEN, and $M_2$ to compare with our FM, and their description is given in introduction section. SML was used by Nayar and Nakagawa (1994), Subbarao et al. (1993) and Ahmad et al. (2005a,b) for calculating initial depth before approximating it with their techniques; GLV was used by Asif et al. (2001) before applying neural networks.

The performance of the proposed focus measure is compared with these methods by using RM and AM. Three object points from each test object; simulated cone, LCD-filter and coin were considered for experiments. We fitted the obtained focus curves to the Gaussian model and rescaled the function values to (0, 1). For the object point $(110,110)$ of simulated cone, the 46th frame out of total 97 frames was found to be the best-focused position. The resolution was computed by using seven positions on each side of the best focused position (peak) and for the accuracy metric, error bound is set to 2% of the curve. The resolution computed by the proposed method was 1.1991, which is the smallest among all others. The accuracy value (1.4449) was also found to be the lowest among other methods. The object point $(145,145)$ of LCD filter has the best focused position at 43rd frame out of total 60 frames. While for the coin, the object point $(245,245)$, which was best-focused at 23rd frame out of 68 frames. Table 1 compares the resolution values, whereas the Table 2 shows the comparison for the accuracy values. From these tables it can be concluded that the proposed focus measure provided lowest values for RM and AM. Fig-
Figures 19 and 20 show the normalized resolution and accuracy values for more lucid comparison. Figures 21–23 show the focus curves fitted to the Gaussian model for different focus measures. We can observe that the curves obtained by the proposed focus measure are narrower and sharper near the peak as compared with other focus measures.

Table 3 shows the initial depth map (without applying any approximation technique) comparisons computed by various focus measures. It is clear from Table 3 that the proposed focus measure computed the depth map better in terms of RMSE, Cor., and \( Q \) than that of the previous focus measures. From Table 3, it can be concluded that the initial depth map computed by proposed focus measure has provided 1.97, 4.58, 4.22, and 0.645% better performance than that of the previous focus measure in terms of \( Q \), 1.84, 3.5, 4.8, and 0.11% in terms of RMSE and 0.342, 0.23, 0.5, and 0.13% in terms of Cor.

We also approximated 3D shape through BS by providing initial depth map obtained by SML, GLV, TEN, and \( M_2 \). Table 4 gives the \( Q \), RMSE, and Cor. when BS approximation is applied to the initial depth map computed through SML, GLV, TEN, \( M_2 \) and proposed focus measure. The results of SML, GLV, TEN, \( M_2 \) and proposed focus measure are improved by 0.5, 0.3, 0.3125, 0.4252, and 0.5587% in terms of \( Q \), 1.41, 0.81, 0.87, 1.3%, and 0.32 in terms of RMSE, and 0.51, 0.3, 0.332, and 0.6% in terms of Cor. The value for RMSE, Cor., and \( Q \) (before and after proposed method on the various focus measures) are plotted in Figures 24–26, which provide better comparison. The figures and the tables show that the proposed method improved the depth map computed by previous focus measures (and proposed focus measure) considerably.

Table 3. Comparison of initial-depth-map, computed by different focus measures with proposed focus measures for simulated cone

<table>
<thead>
<tr>
<th>Focus measures</th>
<th>( Q )</th>
<th>RMSE</th>
<th>Cor.</th>
</tr>
</thead>
<tbody>
<tr>
<td>SML</td>
<td>0.7196</td>
<td>6.6918</td>
<td>0.9655</td>
</tr>
<tr>
<td>GLV</td>
<td>0.7017</td>
<td>6.8061</td>
<td>0.9666</td>
</tr>
<tr>
<td>Ten</td>
<td>0.7041</td>
<td>6.9001</td>
<td>0.9641</td>
</tr>
<tr>
<td>( M_2 )</td>
<td>0.7291</td>
<td>6.5761</td>
<td>0.9876</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.7338</td>
<td>6.5689</td>
<td>0.9688</td>
</tr>
</tbody>
</table>

Table 4. Comparison of depth-map approximated by Bezier surface with different focus measures for simulated cone

<table>
<thead>
<tr>
<th>Focus Measure + BS</th>
<th>( Q_{BS} )</th>
<th>RMSE_{BS}</th>
<th>Cor._BS</th>
</tr>
</thead>
<tbody>
<tr>
<td>SML</td>
<td>0.7231</td>
<td>6.5977</td>
<td>0.9704</td>
</tr>
<tr>
<td>GLV</td>
<td>0.7037</td>
<td>6.7511</td>
<td>0.9695</td>
</tr>
<tr>
<td>Ten</td>
<td>0.7063</td>
<td>6.8403</td>
<td>0.9673</td>
</tr>
<tr>
<td>( M_2 )</td>
<td>0.7322</td>
<td>6.5494</td>
<td>0.9718</td>
</tr>
<tr>
<td>Proposed</td>
<td>0.7379</td>
<td>6.5481</td>
<td>0.9744</td>
</tr>
</tbody>
</table>

Computational Complexity

The proposed SFF method comprises of two parts (i) focus measure and (ii) BS approximation. The proposed focus measure is simple to compute and faster than existing methods. We computed the focus value of object point \((110,110)\) with neighborhood of window size \(5 \times 3\) for all focus measures using Matlab 7.0.1 on Pentium-IV machine. The time calculated for the proposed focus measure was 0.031 s, whereas SML, GLV, TEN, and \( M_2 \) took 0.219, 0.226, 0.235, and 0.203 s, respectively. However, the BS approximation is computationally expensive and its complexity varies with the selection of degree and length of parameters of polynomials. We applied second-order polynomials and the proposed algorithm iterates \( X^3 Y \) times, where as the conventional methods search the whole focus volume i.e., they execute \( n(X \times Y) \) times, where \( n \) is the number of images in the sequence. Hence, the overall complexity of the proposed approach is comparable with existing methods. However, choosing a higher degree...
CONCLUSION

In this article, we have proposed a new focus measure especially for the shape reconstruction using focus based passive method (SFF); and 3D shape approximation using BSs. The proposed scheme is tested by using synthetic and real microscopic objects and obtained results has been compared with existing methods. Comparative analysis has shown the effectiveness of the proposed scheme. The study can be summarized as follows:

- We have developed a simple but robust algorithm to calculate best focus measure based on pixel intensities only. The initial depth map is computed by finding the frame number corresponding to maxima of the modified pixel intensity vector.
- The proposed FM is specially designed to reduce the complexity of overall system. Thus, it is fast, computationally efficient and more precise.
- We have proposed a new approximation method for SFF using BS approximation (SFF.BS). The proposed method is more precise as compared with previous methods. The results are compared, using RM and AM (for focus measure), and RMSE, Q, and Cor. (for depth map).
- The results have shown noteworthy improvement by proposed method. Furthermore, results and comparison showed that the SFF.BS method can be applied to the initial depth map computed by any other focus measure, and it improves the (3D recovered) shape significantly.
- The initial depth map obtained by using the proposed FM is refined by computing a BS of each point using its eight neighbors. This refined depth map is taken as the final depth map of the object.

REFERENCES

A NOVEL METHOD FOR SFF USING BS APPROXIMATION


