HK Segmentation of 3D Micro-structures Reconstructed from Focus

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Abstract. This paper presents an evaluation of HK segmentation on 3D micro-structures reconstructed from focus. Due to the necessity of 3D shape and surface structure information for a precise micromanipulation, shape of the object is recovered using shape from focus (SFF). In the SFF procedure, using an image sequence, composed of images captured at different focusing levels, focused image of the micro-structure and its shape are acquired. Then the resulting shape, also called range image, is used in HK segmentation method to extract surface curvature information. Experimental results show that this technique works for both synthetic and real data.

Keywords: HK Segmentation, 3D Micro-structures, Image.

1 Introduction

Precise micromanipulation requires 3D shape and surface structure of the manipulated object. Shape information is extracted from images acquired under the optical microscope. In the literature, there are several active and passive methods like structured light, binocular stereo, shape from shading and shape from focus/defocus to extract 3D geometry of the examined object [1]-[5]. The acquisition of the 3D geometry of micro object enables us to apply a curvature-based descriptor to obtain range surface segmentation [6]-[9]. Curvature-based desriptors were used in several applications. Trucco and Fisher evaluated range image segmentation system using estimates of the sign of the mean and Gaussian curvatures (H and K respectively) on a range image of an automobile part [7]. Cantzler and Fisher compared HK and SC (shape index and curvedness) segmentation on range images of several objects, and it resulted that both methods have the same performance [9]. Moreno et.al applied HK segmentation on 3D human face surfaces for face recognition [10]. These papers addressed the problem of extracting surface information from range images of macro scale objects.

In this paper, shape of the objects were recovered using shape from focus approach [1]. The application of this method requires to move an unknown object on a micro-translation stage with respect to the optical microscope in the z-axis. During this process, at each focus level different parts of the object come into focus and give sharp images. A focus measure operator is used to measure the degree of focus at each pixel of images in the image sequence. Depth estimate for each pixel corresponding to an object point is acquired by interpolating a Gaussian curve to the points around the peak value. Using the resulting shape from this process, curvature-based segmentation of the range image is realized. This segmentation enables to learn whether a surface patch of the range image is planar, cylindric, elliptic or hyperbolic. Having acquired a priori shape and curvature information of the micro object will be helpful in 3D micromanipulation.

The paper is organized as follows: Section 2 defines shape from focus and HK segmentation of range images. Section 3 presents experimental results. Finally, Section 4 concludes the paper with some remarks.

2 3D Reconstruction from Focus and HK Segmentation of Range Images

Curvature-based segmentation methods are used in object classification, pose estimation, and computer graphics in macro world applications. Input to the surface-based descriptor in such applications are range images acquired from the laser scanners. In micro domain although it is possible to apply an active sensing method like 3D Laser Scanning Microscope to have range image of the object, due to its cost, a passive sensing method like shape from focus is more feasible. So, initially a range image is acquired from shape from focus and then a curvature-based segmentation method is applied on the image to extract curvature information of the surface patches.

2.1 Shape from Focus

SFF [1] requires several images of the object at different focusing levels to acquire a 3D map of the object. The object is placed on a micro-translational stage under the optical microscope and the stage is translated in the z-direction until images related to entire 3D object becomes de-focused. In this process, the images are captured at discrete focusing levels with a step size of Δd.

Assuming microscope objective as a thin lens, an object point at a distance d_o from lens will form an image at d_i. If the sensor plane is at a distance d_s and $d_s \neq d_i$, then the image will be a circular blob of radius r_b instead of a point. The relation between r_b and the sensor displacement $\lambda = d_s$ - d_i can be given as $r_b = R\lambda/d_i$ where R is the radius of the lens. Using the Gaussian lens law, the blur radius can be reformulated as [2],

$$r_b = Rd_s[\frac{1}{w_d} - \frac{1}{d_o}] \tag{1}$$

where w_d is working distance of the microscope objective. If an object point is at a distance d_o which is equal to w_d then it forms a focused image. The shape of the object can be estimated by recording the stage position which brings a part of the object into focus.

In order to evaluate the degree of focus, a focus measure has to be selected. The focus measure is calculated in a region around each pixel in the image sequence and the operator gives the highest value at the image which object point is in maximum focus. Sum-modified-Laplacian operator is chosen to be used in the experiments since it performs very well for surfaces that produce textured images [3]. The discrete approximation to the modified laplacian (ML) operator is given by

$$\begin{aligned} ML(u,v) &= |2I(u,v) - I(u-step,v) - I(u+step,v)| \\ &\quad + |2I(u,v) - I(u,v-step) - I(u,v+step)| \end{aligned} \tag{2}$$

where step is the variable spacing between the pixels. The SML focus measure at a point (i,j) is computed as the sum of modified Laplacian values, in a small window around (i,j), using only values that are greater than a threshold:

$$F(i,j) = \sum_{u=i-W}^{i+W} \sum_{v=j-W}^{j+W} ML(u,v), \quad if\ ML(u,v) > T \tag{3}$$

where W determines the window size around the pixel (i,j) to compute the focus measure and T is the threshold value. A small window size of 3×3 or 5×5 is used since large window size introduces blur by taking into account more pixel values which might be quite different from the pixel in consideration as mentioned in [4]. Computation of $F(i,j)$ at each pixel in the image sequence forms a focus measure profile from which shape can be estimated using Gaussian interpolation.

2.2 HK Segmentation of Range Images

The result of shape from focus algorithm is in the form of a range image which has the same dimensions with the image of the object. To find shape composition of the visible surface of an object, a curvature-based segmentation has to be applied. HK segmentation, which partitions a range image into regions of homogeneous shape, is a proper method for this classification [6].

This method is based on differential geometry, and it uses the mean curvature H and the Gaussian curvature K. Local surface shape can be estimated using signs of H and K at each pixel as shown in Table 1. Calculation of H and K values in a range image S is done according to the following formulas

$$H = \frac{(1+S_x^2)S_{yy} - 2S_xS_yS_{xy} + (1+S_y^2)S_{xx}}{2(1+S_x^2+S_y^2)^{3/2}} \tag{4}$$

$$K = \frac{S_{xx}S_{yy} - S_{xy}^2}{(1+S_x^2+S_y^2)^2} \tag{5}$$

where S_x, S_y, S_{xy}, S_{xx} and S_{yy} are range image derivatives computed from the convolution of numerical derivative filter with the range image. Before these computations, if there is noise in the image due to quantization or resolution,

Table 1. Shape Classification Scheme

H	K	Local Surface Shape
-/0/+	-	hyperbolic
-	0	convex cylindrical
+	0	concave cylindrical
-	+	convex elliptic
+	+	concave elliptic
0	0	plane

gaussian smoothing has to be applied. In this step, as standard deviation of gaussian filter increases, segmentation estimates get worse [7]. A zero-threshold has to be determined for H and K values since numerical estimates of H and K will not be exactly zero [6]. After the computation of H and K images, each pixel is assigned a shape label according to Table 1.

3 Experimental Results

In this section, first the application of SFF algorithm on synthetic and real data is presented, and then surface shape classification results of the range images, acquired from the application of SFF algorithm, using HK segmentation is given.

3.1 SFF Results

SFF is first evaluated on a synthetic texture image shown in Fig. 1(a). An image sequence is created in which at each focus level a different part of the parabolic object is focused. In the creation of these images, camera defocus PSF was modeled as a 2-D Gaussian function and given by $(1)/(2\pi\sigma^2)exp(-(i^2 + j^2)/(2\sigma^2))$ where σ is the deviation of the Gaussian function [2].

SFF algorithm is applied on the image sequence, some of which shown in Fig. 1(b),(c), corresponding to a parabolic shape created assuming $\Delta d = 25\mu m$ and object height is $500\mu m$. The resulting focused image is shown in Fig. 1(d).

Since the spikes in range image would result in problems at HK segmentation stage, these were detected and replaced with the response of median filtering as it is done in [5]. Resulting range image is shown in Fig. 2.

After the application of SFF on synthetic data,it is also evaluated on real data. The image sequence shown in Fig. 3(a)-(c), which belongs to a solder ball on paper, was captured under an optical microscope. Initially as it is shown in Fig. 3(a), paper in the background is focused. Then, micro-translational stage is moved with a $\Delta d = 50\mu m$ until whole object is scanned (Fig. 3(b), (c)). The implementation of SFF on this image sequence resulted in the following focused image shown in Fig. 3(d). Error correction is also applied to the range image acquired from real data. However, due to the rough surface of the ball, the range image result is not very smooth (Fig. 4). Since the object is observed from above, only half of it can be examined. This is why lower part of 3-D map of the object is a cylinder and the top part is spherical.

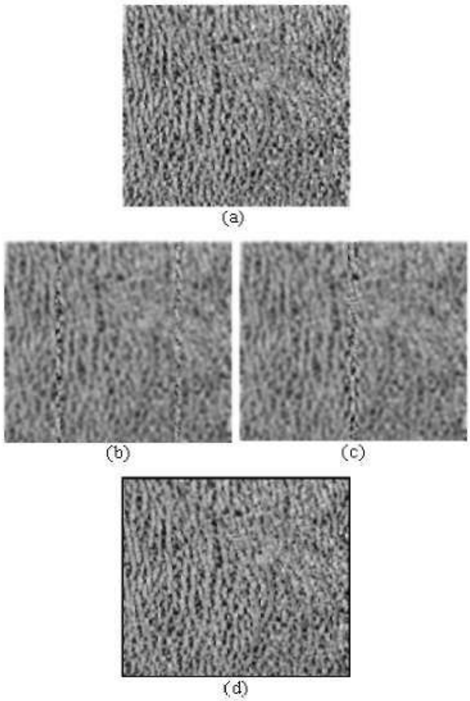

Fig. 1. (a) Original Textured Image (b), (c): Defocused Images in the Image Sequence for SFF (d) Resulting Focused Image from SFF

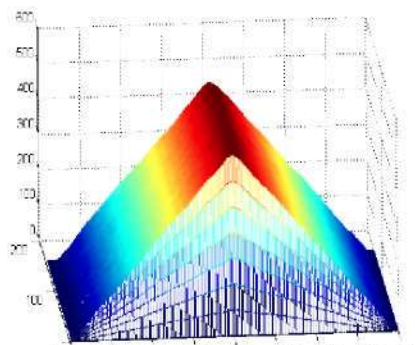

Fig. 2. Resulting Parabolic Range Image from Synthetic Data

3.2 HK Segmentation Results

HK segmentation initially applied on the parabolic profile resulted from the application of SFF on synthetic data to examine the surface structure of the

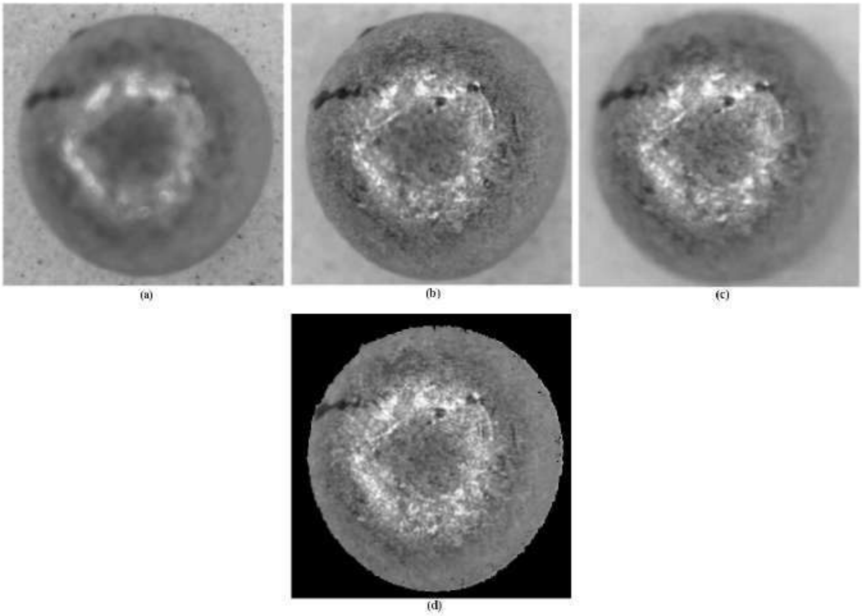

Fig. 3. (a)-(c) Defocused Images of Solder Ball. (d) Resulting Focused Image from SFF.

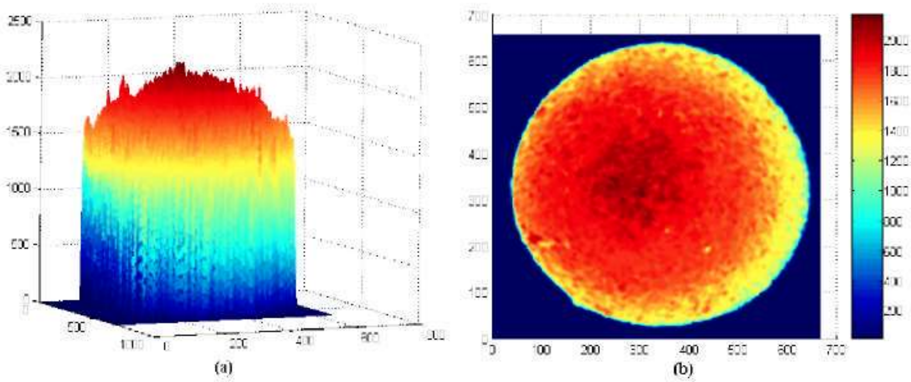

Fig. 4. (a) Solder Ball Range Image (b) Range Image x-y View

parabolic profile. Before the segmentation procedure, gaussian filter with a standard deviation of 1.5 is applied to the range image to smooth the image. Also zero threshold for H and K were determined as 0.03 and 0.0008, respectively. In the resulting segmentation, as it is shown in Fig. 5, left and right of the maximum of the parabola is planar. Although it is expected that the maximum of the surface would be mostly convex cylindric, there are some hyperbolic surface

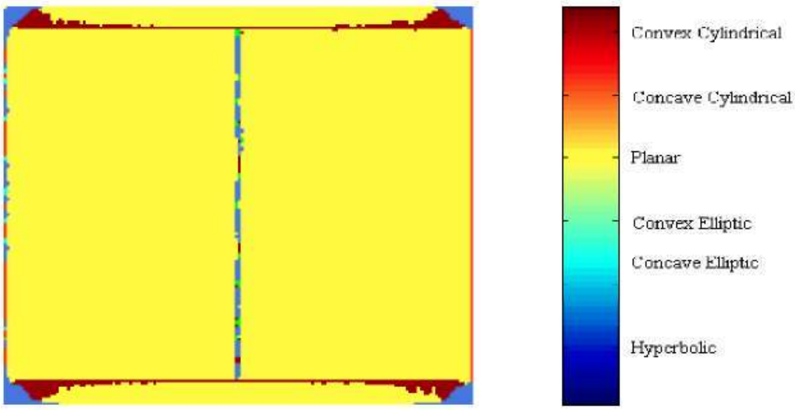

Fig. 5. HK Segmentation of Range Image Result of Synthetic Data

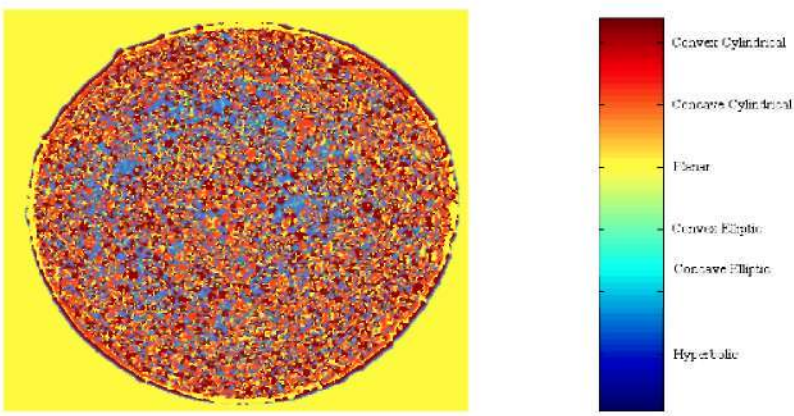

Fig. 6. HK Segmentation of Range Image Result of Real Data

patches detected by HK segmentation. This is due to the errors generated by SFF procedure. Also the edges of the surface are detected as convex cylindrical due to the fact that Gaussian smoothing of the range image results in a convex cylindrical shape at the intersection of parabolic object and background.

Gaussian smoothing was also applied to the SFF result and a zero threshold for H and K was determined. Then surface structure of the solder ball was acquired by applying HK segmentation on the range image result of SFF as it is shown in Fig. 6. Due to the roughness of the surface, mostly concave cylindric patches were detected on the upper surface of the object. There were also some hyperbolic patches again as a result of rough surface structure. However, if the range image was an image of a smooth sphere, it would be convex elliptic.

4 Conclusion

We have shown that HK segmentation can be used on the 3D maps obtained from Shape from Focus (SFF) method to extract surface curvature information. Experimental results show that HK segmentation technique, which was used for surface shape classification of range images of macro-scale objects captured using laser range scanners, can also be used to classify surface curvature and hence related micro-structures. These procedures will be important for classifying/recognizing 3D micro-structures to be manipulated.

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