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Shape from Silhouette and Neural Network Based Optimization

Haruki Kawanaka*
Graduate School of Engineering,
Nagoya Institute of Technology

Yuji Iwahori†
Center for Information and Media Studies
Nagoya Institute of Technology

Akira Iwata‡
Faculty of Engineering
Nagoya Institute of Technology

Abstract

In this paper, a new approach is proposed to recover the shape for the restricted observation with the limited rotation angle. This is achieved by combining Shape-from-silhouette and the Hopfield neural network based optimization technique.

Under the condition that the number of the observed images is restricted with the limited rotation angle, the original Shape-from-silhouette gives poor result, while the HF-NN optimization gives the high performance with the exact shape through the formulation of the partial derivatives of height and gradient.

Further, the approach is quite empirical in that no explicit assumptions are used for the specific surface reflectance function. RBF neural network is used to estimate the image irradiance (i.e. reflectance map R) in the optimization process.

Then, computer simulation evaluates the accuracy of our method. Moreover, the experiment by the real object is shown and the effectiveness of the proposed method is demonstrated.

1 Introduction

In computer vision, it is an important problem to obtain the $3D$-shape from the observed images. Shape-from-silhouette [1] is a method to recover the shape from many images taken at many view points for an object. In general, Shape-from-silhouette needs the observation from 360 degrees rotation with the small rotation angle to get the detailed shape. However it has the problem to catch the local concave shape. When the movement of a viewpoint is restricted or the fine observation is difficult, the resulting error becomes very large.

In this paper, a new approach is proposed to recover the shape for the restricted observation with the limited rotation angle. This is achieved by combining Shape-from-silhouette and the neural network based optimization technique. Here, Hopfield like Neural Network [2] (HF-NN) is used for the optimization. HF-NN uses the convex full of the object obtained from Shape-from-silhouette as the initial state. Then, it optimizes the energy function. In this paper, we formulate the energy function for the shape recovery to get the exact shape using the shading information.

The proposed approach takes the advantages that it can catch the detailed shape from the limited number of the observed images and it is not necessary to take the observation from the whole rotation. The method obtains the surface data not the volume data. HF-NN also has an advantage to save the calculation time with a parallel computer. Further, the approach is quite empirical in that no explicit assumptions are used for the specific surface reflectance function. Radial basis function neural network (RBF-NN) is used to estimate the image irradiance in the optimization process.

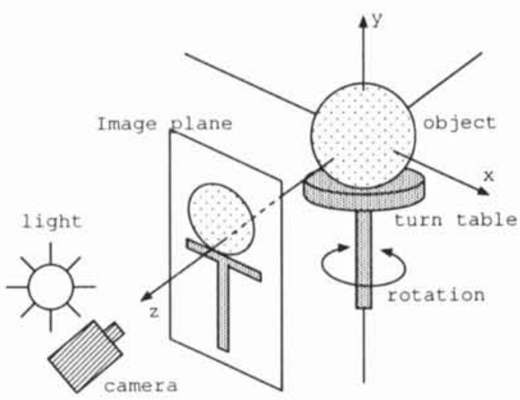

Figure 1: Observation System

2 Obtaining $3D$ shape

2.1 Convex Full from Silhouette

Fig.1 shows the observation system. A camera and a light source are fixed, instead, an object is put on a turntable. Parallel light source is illuminated from the viewing direction and the orthographic projection is assumed.

Shape-from-silhouette tries to get the shape using the inverse projection from the silhouette of each image, and the resulting shape becomes strictly a convex full of the object under the condition that the range of the rotation is restricted and the rotation step is taken large. This is shown in Fig.2.

*Address: Gokiso-cho, Showa-ku, Nagoya, 466-8555, Japan. E-mail: haruki@center.nitech.ac.jp

†E-mail: iwahori@center.nitech.ac.jp

‡E-mail: iwata@elcom.nitech.ac.jp

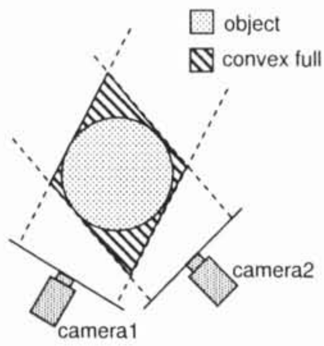

Figure 2: Reconstruction from Silhouette

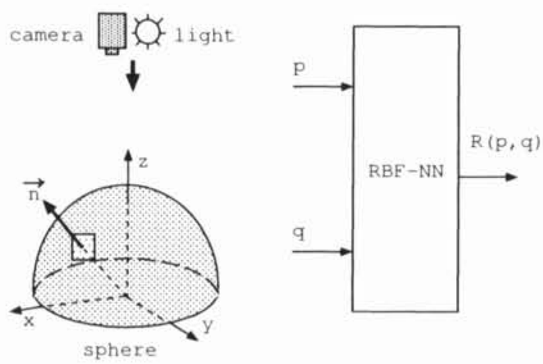

Figure 3: Learning Reflectance Function of Sphere Using Radial Bases Function Neural Network

2.2 Empirical Estimation of Surface Reflectance

The estimation of the image irradiance from the surface gradient parameters (p, q), where $p = \partial z/\partial x$ and $q = \partial z/\partial y$, can be empirically realized using RBF-NN. RBF-NN is used to learn the mapping of (p, q) to estimate the reflectance map $R(p, q)$ for many points on a sphere which has the same reflectance property as the target object, as shown in Fig.3. Thus, RBF-NN can be applied to treat any surface reflectance $R(p, q)$ without assuming any specific parametric function for the surface reflectance.

2.3 HF-NN Optimization

2.3.1 Energy Function for Optimization

Fig.4 shows the architecture of HF-NN. HF-NN is a mutual combination type neural network, and the combination between neurons is symmetric. The optimization using HF-NN is done by updating the process so that the partial derivatives of the energy function with each variable become 0 [3].

Here, the energy function is formulated according to the photometric constraint and the additional standard regularization [4]. Let the total energy function be E in equation (1).

$$E = C_1 E_1 + C_2 E_2 + C_3 E_3 \tag{1}$$

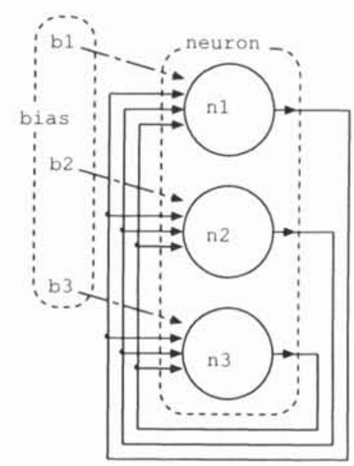

Figure 4: Hopfield like Neural Network

$$E_1 = \iint_D \left\{ \left(\frac{\partial p}{\partial x}\right)^2 + \left(\frac{\partial p}{\partial y}\right)^2 + \left(\frac{\partial q}{\partial x}\right)^2 + \left(\frac{\partial q}{\partial y}\right)^2 \right\} dxdy$$

$$E_2 = \iint_D \{I(x, y) - R(p, q)\}^2 \, dxdy$$

$$E_3 = \iint_D \left\{ \left(\frac{\partial z}{\partial x} - p\right)^2 + \left(\frac{\partial z}{\partial y} - q\right)^2 \right\} dxdy$$

where $I(x, y)$ is the observed image irradiance at (x, y). C_1, C_2 and C_3 are regularization parameters. D means the target region. E_1 is defined as the smoothness constraint. E_2 is the error between $R(p, q)$ and $I(x, y)$. E_3 is the error between the first partial derivatives of z and p, q.

The corresponding equations of the partial derivatives of the energy function with each variable can be derived as follows.

$$\frac{\partial z}{\partial t} = -\frac{\partial E}{\partial z} = -\frac{\partial E_3}{\partial z}$$

$$\frac{\partial E_3}{\partial z} = -2C_3 \left(\frac{\partial^2 z}{\partial x^2} - \frac{\partial p}{\partial x} + \frac{\partial^2 z}{\partial y^2} - \frac{\partial q}{\partial y} \right)$$

$$\frac{\partial p}{\partial t} = -\frac{\partial E}{\partial p} = -\left(\frac{\partial E_1}{\partial p} + \frac{\partial E_2}{\partial p} + \frac{\partial E_3}{\partial p} \right)$$

$$\frac{\partial E_1}{\partial p} = -2C_1 \left(\frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} \right)$$

$$\frac{\partial E_2}{\partial p} = -2C_2 \left(I(x, y) - R(p, q) \right) \frac{\partial R(p, q)}{\partial p}$$

$$\frac{\partial E_3}{\partial p} = -2C_3 \left(\frac{\partial z}{\partial x} - p \right)$$

$$\frac{\partial q}{\partial t} = -\frac{\partial E}{\partial q} = -\left(\frac{\partial E_1}{\partial q} + \frac{\partial E_2}{\partial q} + \frac{\partial E_3}{\partial q} \right)$$

$$\frac{\partial E_1}{\partial q} = -2C_1 \left(\frac{\partial^2 q}{\partial x^2} + \frac{\partial^2 q}{\partial y^2} \right)$$

$$\frac{\partial E_2}{\partial q} = -2C_2 \left(I(x, y) - R(p, q) \right) \frac{\partial R(p, q)}{\partial q}$$

$$\frac{\partial E_3}{\partial q} = -2C_3 \left(\frac{\partial z}{\partial y} - q \right)$$

2.3.2 Optimization Process

The convex full (volume data) obtained from Shape-from-silhouette is transformed into the surface data using Marching Cubes (MC) [5].

Let height distribution be the initial vector of z of the above surface data of the convex full. The initial vectors of p, q are also given as the first partial derivatives of z with respect to x and y.

As long as an output function is a non-decreasing function and time change of the internal state of each neural network unit is given by the negative gradient of the energy function, the energy function always decreases with the updating process.

Optimization is applied for each image. Once optimization is done for an image, the following optimization is applied for another image among n-images under the different rotation angles. Thus, the optimization process is repeated for each image alternately. Optimization process is terminated when z-distribution becomes almost the same as that of 1 step before.

3 Experiments

The performance was evaluated for both the synthetic images and the real images. Each input image has 8-bits gray scale with 128×128 pixel. Three images are used under the rotation angle $\theta = 0, \pm 10$ degrees. Fig.5 shows one of input images (at $\theta = 0$). As shown in Fig.5, let three spheres arranged horizontally be the target object to recover the shape.

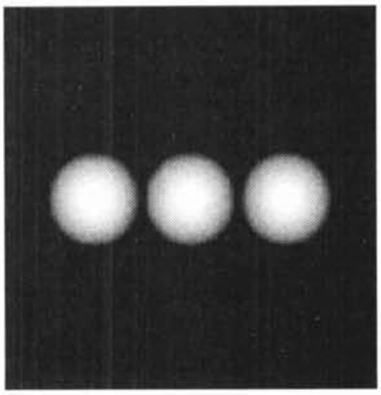

Figure 5: Input Image($\theta = 0$)

Fig.6 represents the surface data converted from the volume data obtained by Shape-from-silhouette using the MC. Then, this surface data is set as the initial vector for the HF-NN optimization. During the optimization, RBF-NN is used to realize the surface reflectance R of a target object.

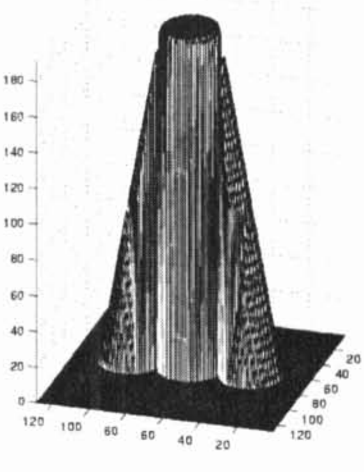

Figure 6: Initial Vector

Fig.7 shows the result of HF-NN optimization for the synthetic image. The proposed method can recover the detailed shape up to the concave area which cannot be caught by Shape-from-silhouette. Table 1 shows the accuracy of the recovered z-distribution. The average of error, the rate of error for the height, the standard deviation (SD) and the mean square error (MSE) were evaluated. It is shown that the result through the energy optimization works effectively from the initial state by Shape-from-silhouette.

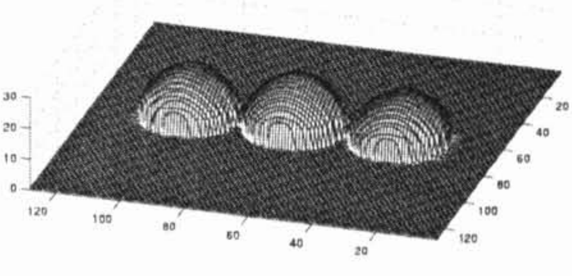

Figure 7: Recovered Shape

Here, the optimization process for the image sequence of $\{0, \theta, \theta, 0, -\theta, -\theta\}$ is defined as one step. Then the optimization up to about 70 step is shown in Fig.8. The implementation has been performed with Matlab on the PC (Athlon MP 1.2GHz, 1Gbyte main memory). The time to the convergence costs about 190 minutes.

Next, the experiment for the real images was done. Fig.9 is one of the input images. Fig.10 shows the initial vector obtained by the Shape-from-silhouette.

Fig.11 shows the optimized result through the HF-NN. Although some error has occurred in recovering under the effect of the contrast and defocus of input images, it is shown that the shape of the object can be almost recovered.

In addition, the method is applicable for the case that the surface is almost smooth and continuous. The optimization uses the smoothness constraint, the integration to obtain z from p, q and the derivation to obtain p, q from z simultaneously. Thus, the method can further improve the result of Shape-from-silhouette with the high performance.

4 Conclusion

In this paper, we proposed a new approach to recover the shape using Shape-from-silhouette and HF-NN based optimization.

Under the condition that the number of the observation is restricted with the limited rotation angle, the original Shape-from-silhouette gives poor result, while

Table 1: Evaluations of Accuracy

	Initial	Result
$max(z)$	191.5	18.32
$\overline{e} = \overline{\lvert z - z_t \rvert}$	100.5590	1.069
$\overline{e}/r$	6.291	0.06687
SD	68.91	0.851
MSE	1.486×10^4	1.867

z : height distribution, z_t : theoretical value of height distribution, $\overline{e}$: mean absolute error, r : radius($=16$)

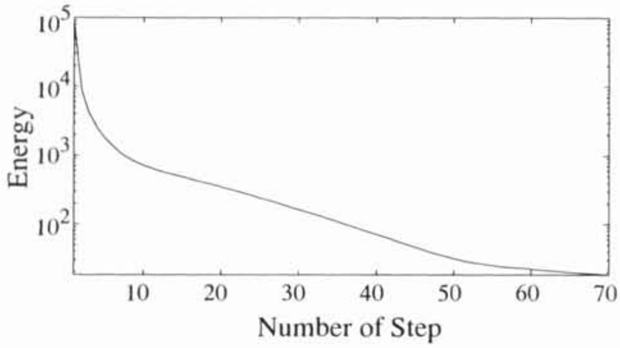

Figure 8: Energy Changes

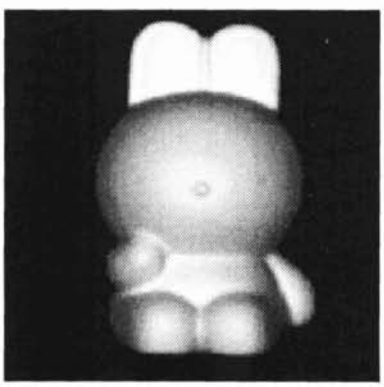

Figure 9: Input Image($\theta = 0$)

the HF-NN optimization gives the high performance with the detailed shape through the formulation of the partial derivatives of height and gradient. The proposed method also treats the surface reflectance empirically. This is realized by RBF-NN. No assumptions for surface reflectance function are used under the limited condition for the observation with a fixed camera.

The proposed method has a potential for other applications such as the SEM (Scanned Electron Microscope). This is because the similar condition holds for the observation of SEM images. The application of the method to such an environment remains as the future subject.

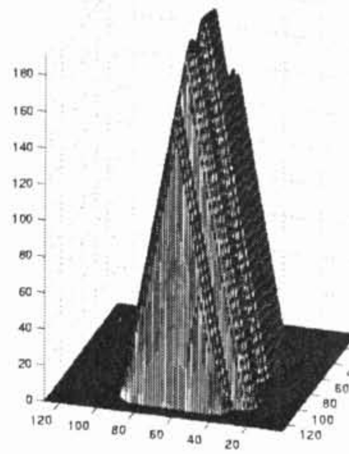

Figure 10: Initial Vector

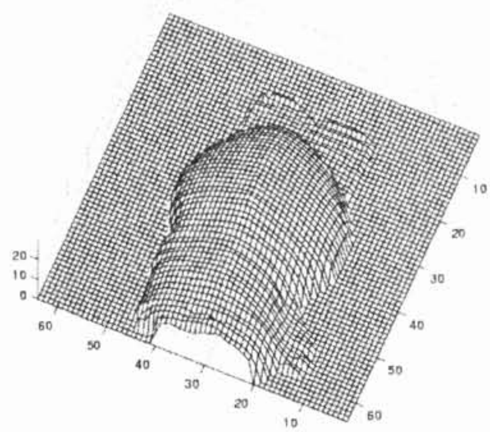

Figure 11: Recovered Shape

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