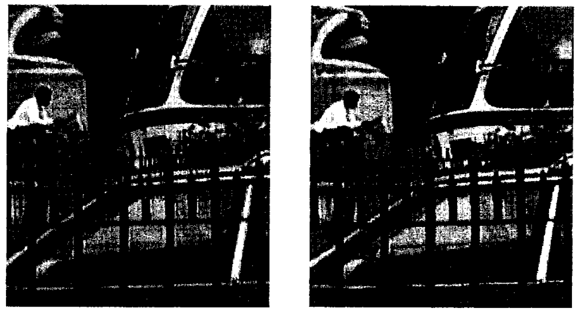
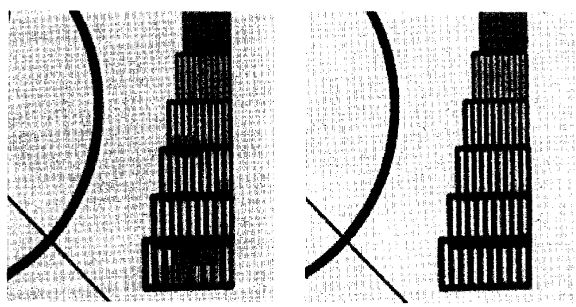


a b

Fig. 2 *Comparison of performance in terms of blocking artifacts ('Bus' sequence)*

a With conventional MCI
b With adaptive MCI



a b

Fig. 3 *Comparison of performance in terms of blocking artifacts ('Grates' sequence)*

a With conventional MCI
b With adaptive MCI

19 November 2001
Electronics Letters Online No: 20020306
DOI: 10.1049/el:20020306

S.-H. Lee and S. Yang (*Digital Media R&D Center, Samsung Electronics Co. Ltd., Suwon 442-742, Korea*)

References

1 CAFFORIO, C., ROCCA, F., and TUBARO, S.: 'Motion compensated image interpolation', *IEEE Trans. Commun.*, 1980, **38**, (2), pp. 215–222
2 OJO, O.A., and DE HAAN, G.: 'Robust motion-compensated video upconversion', *IEEE Trans. Consum. Electron.*, 1997, **43**, (4), pp. 1045–1056
3 HILMAN, K., PARK, H.W., and KIM, Y.: 'Using motion-compensated frame-rate conversion for the correction of 3:2 pulldown artifacts in video sequences', *IEEE Trans. Circuits Syst. Video Technol.*, 2000, **10**, (6), pp. 869–877
4 DE HAAN, G., and BIEZEN, P.W.A.C.: 'An efficient true-motion estimator using candidate vectors from a parametric motion model', *IEEE Trans. Circuits Syst. Video Technol.*, 1998, **8**, (1), pp. 85–91

Conformal Snake algorithm for contour detection

S.Y Lam and C.S. Tong

A novel and effective modification of the original Snake algorithm is proposed. The modification can improve the capability of the algorithm to detect boundaries with sharp corners or concave parts without the need to introduce external forces. The essential idea is to apply conformal mapping to transform the image so that the object boundary in the new domain can be captured by the Snake algorithm.

Introduction: The active contour model (Snake) [1] has been successfully employed in contour detection for object recognition, computer vision, computer graphics and biomedical image processing. Although the original Snake algorithm has been widely adopted in contour detection, it still has some difficulty in locating an object boundary having concave parts. This problem has been studied by many researchers and authors and most of their approaches involve inserting an external force which often requires fine-tuning of many parameters to the model [2, 3]. In this Letter we propose a new method called the conformal Snake algorithm. To illustrate the idea, suppose we wish to locate the boundary of an object in Fig. 1. First, we use conformal mapping [4] to transform the image so that the object boundary in the transformed domain is now convex, and the usual Snake algorithm can then be applied to obtain this boundary. We then apply inverse transform to the boundary to obtain the sought-after contour. In practice, we do not know what the required contour is, so we apply the idea in an iterative fashion.

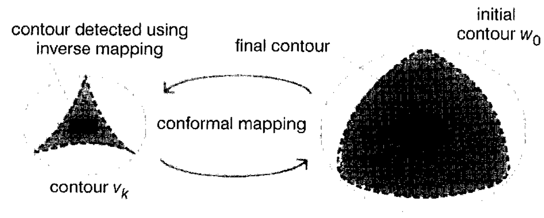


Fig. 1 *Conformal mapping*

Original Snake model: The mechanism of the Snake model is to minimise an energy function called E_{snake} defined as follows. Let $v(s)$ be a smooth parametric curve with parameter $s \in [0, 1]$, then

$$E_{snake}(s) = \int_{\Omega} (E_{int}(v) + E_{image}(v) - E_{ext}(v))ds \quad (1)$$

where $E_{int}(v)$ represents the internal energy and is given by

$$E_{int}(v) = \frac{1}{2}\{\alpha|v_s(s)|^2 + \beta|v_{ss}(s)|^2\} \quad (2)$$

where v_s and v_{ss} are the first- and second-order derivative of the curve $v(s)$ with respect to s. α and β are the scaling factors controlling these two terms.

E_{image} represents the gradient of the image $I(x, y)$ on $v(s)$ and is given by

$$E_{image} = -k_i|\nabla I|^2 \quad (3)$$

where k_i adjusts the magnitude of $|\nabla I|^2$. E_{ext} is an external force which is optional.

A curve $u(s)$, which is the final solution in boundary detection, can be obtained through the optimisation process

$$E_{snake}(u) = \min_{v \in C^2[0,1] \times C^2[0,1]} [E_{snake}(v)] \quad (4)$$

After the optimisation process and adding a backward time step, the Snake algorithm becomes an iterative method and the formula is

$$\frac{\partial v}{\partial t} - \alpha v_{ss} + \beta v_{ssss} + \frac{\partial E_{image}}{\partial s} = 0 \quad (5)$$

By taking finite difference and rewriting it in matrix form, we obtain

$$[(A + \gamma \mathbf{I})x_t \quad (A + \gamma \mathbf{I})y_t] = \gamma v_{t-1} + F(v_{t-1}) \quad (6)$$

where $v_t = [x_t, y_t]$ is the coordinate of the contour. A is the matrix representing the linear operator of

$$-\alpha\frac{\partial^2}{\partial s^2} + \beta\frac{\partial^4}{\partial s^4}$$

after taking finite difference and $\mathbf{I}$ is the identity matrix. γ is the time step and

$$F(v_t) = \left[\frac{\partial E_{image}(v_t)}{\partial x}, \frac{\partial E_{image}(v_t)}{\partial y}\right]$$

Conformal Snake algorithm: The way to perform conformal mapping in the Snake algorithm is now discussed. Let $v^k(s)$ and $u^k(s)$ be the initial and final contour, respectively, after applying the Snake algorithm kth times, and let $v^{k+1}(s) = u^k(s)$ and $h^k(s) = v^k(s) - v^0(s)$ where $v^0(s)$ is the initial contour given by user and $k = 0, 1, 2, 3, \ldots$. A first-order quantisation for the transform g is proposed as

$$w^k(s) = g(v^k(s)) = v^k(s) - h^k(s) = v^0(s) \tag{7}$$

$$J(w^k(s)) = F(g^{-1}(w^k(s))) \qquad \forall s \in \Omega = [0, 1] \tag{8}$$

where $w^k(s)$ is the contour in the new transformed domain. By choosing the initial contour $v^0(s)$ to be convex, the transform g will expand the current contour and render it more convex. The function g is to map the contour $v^k(s)$ to $v^k(s)$. $J(w^k(s))$ is the image force in the domain $w^k(s)$.

The idea of the proposed method is shown in Fig. 1. At first, the Snake algorithm is applied to obtain an outline contour of the object. Conformal mapping is applied and the contour together with the image is mapped from left to right in Fig. 1. The Snake algorithm is again performed. As the contour shrinks, the image energy is changed iteratively. At each step of the Snake, inverse mapping is applied to the contour $w^k(s)$ to update the image force. After that, the contour is transferred back to the domain $w^k(s)$. It should be noted that the contour $w^k(s)$ remains unchanged while the information of image force is being updated. By repeating the above process, the final contour can be detected and it is represented in Fig. 1 by the dashed line.

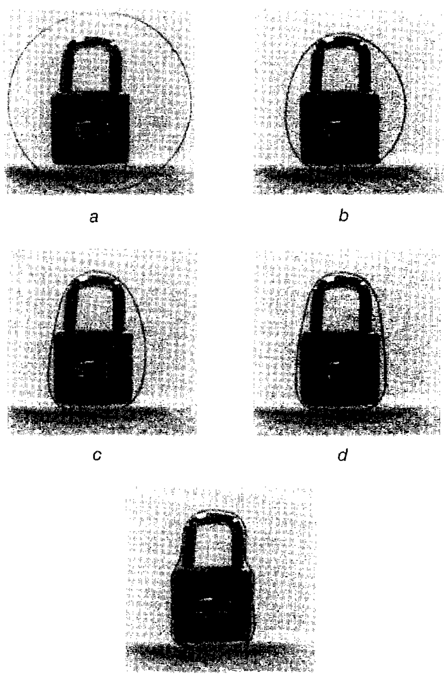


Fig. 2 *Conformal Snake algorithm*
Parameters: $alpha = 1$, $beta = 0.5$, $k_i = 1$
a Initial contour
b Outline contour u^0
c Contour u^2
d Contour u^4
e Final contour u^24

The proposed method is implemented through the following mathematical equations. Assume that the Snake algorithm has applied $(k-1)$th times and the final contour $u^{k-1}(s)$ is obtained. The Snake algorithm is now applied kth times and it becomes

$$((A + \gamma \mathbf{I})x_t^k \quad (A + \gamma \mathbf{I})y_t^k) = \gamma v_{t-1}^k + F(v_{t-1}^k) \tag{9}$$

with initial contour $v^k(s) = [x_0^k(s), y_0^k(s)] = u^{k-1}(s)$. Taking conformal mapping, the initial contour becomes $g(v^k(s)) = w^k(s)$. The equation is written as:

$$\begin{aligned}((A + \gamma \mathbf{I})\xi_t^k \quad (A + \gamma \mathbf{I})\eta_t^k) &= \gamma w_{t-1}^k + J(w_{t-1}^k) \\ &= \gamma w_{t-4}^k + J(w_{t-1}^4)\end{aligned} \tag{10}$$

where $w^k(s) = (\xi, \eta)$. After the Snake algorithm converges, inverse mapping of (7) is applied to obtain the resultant curve $u^k(s)$. By repeating the above process, the contour for the object can be detected.

Experimental results and conclusion: The conformal Snake algorithm is tested using the image of a lock. From Fig. 2*a*, an initial contour $v^0(s)$ is given by the user. The Snake algorithm is applied and an outline contour u^0 for the object is detected in Fig. 2*b*. The process of the conformal mapping is performed and shown in Figs. 2*a*–*e*. The final contour for the object is shown in Fig. 2*e*. The Snake algorithm is applied 25 times in total. In conclusion, the proposed algorithm can locate the concave parts of an object effectively without introducing cumbersome external force.

Acknowledgment: This work was supported in part by a Faculty research grant of Hong Kong Baptist University FRG/99-00/I-43.

7 January 2002
Electronics Letters Online No: 20020335
DOI: 10.1049/el:20020335

S.Y. Lam and C.S. Tong (*Department of Mathematics, Hong Kong Baptist University, Hong Kong*)

E-mail: abdelrafik.malki@univ-rouen.fr

References

1 KASS, M., WITKIN, A., and TERZOPOULOS, D.: 'Snakes: active contour models', *Int. J. Comput. Vision*, 1988, **1**, pp. 321–331
2 WONG, Y.Y., YUEN, P.C., and TONG, C.S.: 'Segmented Snake for contour detection', *Pattern Recognit.*, 1998, **31**, pp. 1669–1678
3 COHEN, L.D.: 'On the active contour models and balloons', *CVGIP, Image Underst.*, 1991, **53**, pp. 211–218
4 FISHER, S.D.: 'Complex variables' (Wadsworth & Brooks/Cole Advanced & Software, Pacific Grove, CA, 1986), 2nd edn.

Refinement method for structure from stereo motion

Sung-Kee Park and In So Kweon

A new method for overcoming bas-relief ambiguity, using calibrated stereo image sequence, is presented. The proposed method uses a direct method for motion estimation as initial guess, and refines both stereo and motion displacement with sub-pixel accuracy. Experimental results show that the proposed algorithm improves estimation accuracy under such ambiguity.

Introduction: The structure from motion, assuming small motion such as optical flow and a direct method, inevitably has motion ambiguity between translation and rotation. For solving this, conventional methods [1, 2] adopt a single line methodology; first they try to find exact corresponding points with only image brightness, and motion parameters and scene depths are then estimated on the basis of it. However, considering that the previous corresponding methods can have large errors and it is difficult to define an error model [3], the single line methods cannot improve such ambiguity even though robust statistical estimaton is introduced. Therefore, on the assumption that corresponding points and motion estimation have to be iteratively refined, we propose a new method for improving ambiguities using stereo image sequence.

Proposed refinement method: Fig. 1 shows stereo motion and basic notations. In calibrated stereo, its motion, **w** and **t**, can be estimated by the direct robust method [4]. However, although the previous methods try to find global minimum, only its vicinity can be guaranteed; i.e. because the shape of cost function in estimating motion parameters under bas-relief ambiguity are like a narrow diagonal valley [3]. Thus, it is essential to refine the correspondence for improving such ambiguity.