

Controlling B-Spline Snake Behavior using Particle Swarm Optimization

Habibullah Akbar^{*}, Nanna Suryana, Shahrin Sahib

Faculty of Information and Communication Technology

Universiti Teknikal Malaysia Melaka

Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

E-mails: habibbrown@gmail.com, nsuryana@utem.edu.my, shahrinsahib@utem.edu.my

^{*}Corresponding author

Received: July 19, 2012

Accepted: September 12, 2012

Published: September 15, 2012

Abstract: Traditional active contour models are hardly convergence to object boundaries where subjective contour and complex background appear. One of the main reasons is because the weighted combination of image energy functions can produce totally different B-Spline snake behaviors. Some efforts have been focused to improve the external energy forces but also lead to higher computational cost. In this research, an approach based on the particle swarm optimization is utilized to control the snake behavior without the necessity of computing the additional information. In the proposed approach, the weighted parameters are optimized using particle swarm optimization by evaluating control points of B-Spline snake in the image energy terms. This method enables the snake to initialize the image energy coefficient automatically and in more convenient way. Experimental results demonstrate that the proposed method can improve the snake behavior.

Keywords: Active contour models, Snake behavior, Particle swarm optimization, Image energy, B-Spline.

Introduction

Contour estimation problems in image segmentation are very crucial in biomedical applications such as pathological diagnosis, computer-aided surgery and anatomical structure studies. In contrast to industrial applications, the estimation procedures require lots of assumptions due to poor quality of images. Particularly, active contour models or snakes, originally introduced by Kass et al. [1], have been growing over the last two decades and extensively used in medical image segmentations. The basic concept is to propagate a predetermined control points toward edge, line and subjective contour by means of energy minimization. Snakes model have been proven to be powerful for medical practitioners and experts when *a priori* knowledge of object's shape is known [2].

One of the main disadvantages of traditional snake models is poorly convergence to object boundaries where subjective contour and complex background appear. The main reason is because the weighted combination of image energy functions can produce totally different B-Spline snake behaviors. Some efforts have been focused on improving the internal and external energy forces [3–8] that can produce better results in comparison to Kass model [1]. Unfortunately, these models do not solve the automatic segmentation problems because many parameters have to be determined manually. Consequently, this problem limits the applications of active contour models in biomedical research areas. Moreover, the manual segmentation processes are time consuming for real medical routines [9]. In fact, fully automatic segmentation algorithm in medical imaging is remain unsolved. Therefore, semi automatic algorithm offers

more convenient way than manual procedure and widely accepted for current trend.

Recently, bio-inspired optimization algorithms have started to receive considerable attention in active contour models. Tseng et al. utilize particles swarm optimization (PSO) to search the optimal snake energy parameters [10]. A new local energy function which corresponds to each control point is defined as an objective function to be minimized. On the other hand, honey bee mating optimization is proposed for total energy minimization for active contour models [11]. The results of these optimization approaches are more precise and computationally cheaper than traditional methods. However, the model parameters still require manual determination from users.

In contrast to Tseng model, this research proposed different scheme for snake algorithms. Instead of utilizing PSO algorithm to search the optimal spline control points, the proposed method used PSO to search optimal value of energy coefficients automatically. The PSO is used to control the snake behavior without the necessity of computing the additional information. In the proposed approach, the weighted parameters are optimized using PSO by evaluating control points of B-Spline snake in the image energy terms. This method enables the snake to initialize the image energy coefficient automatically and in more convenient way. Experimental results demonstrate that the proposed method can improve the snake behavior.

Snakes Algorithm

In parametric models, snake is defined using a curve $p(s) = [x(s), y(s)]$, $s \in [0, 1]$. Deformation is performed by minimizing energy function E_{snake} .

$$E_{snake} = \int_0^1 E_{snake}(p(s)) ds = \int_0^1 (E_{internal}(p(s)) + E_{external}(p(s))) ds \quad (1)$$

The first energy component is purely based on the shape of the contour while the second energy component depends on intensity level of image.

$$E_{internal} = \frac{1}{2} \left(\alpha(s) \left| \frac{\partial p(s)}{\partial s} \right|^2 + \beta(s) \left| \frac{\partial^2 p(s)}{\partial s^2} \right|^2 \right) \quad (2)$$

The internal energy term contains first-order and second-order derivatives of $p(s)$. Coefficients $\alpha(s)$ and $\beta(s)$ play the role of snake's tension and rigidity properties.

$$E_{external} = w_{line} E_{line} + w_{edge} E_{edge} + w_{term} E_{term} \quad (3)$$

The external energy term is linear combination of three components which are derived from the image properties:

$$E_{line} = I(x, y) \quad (4)$$

$$E_{edge} = -(G_{\sigma} * \nabla^2 I)^2 \quad (5)$$

$$E_{term} = \frac{C_{yy}C_x^2 - C_{xy}C_xC_y + C_{xx}C_y^2}{(C_x^2 + C_y^2)^{\frac{3}{2}}} \quad (6)$$

The line energy is image intensity $I(x, y)$. The edge energy is computed using the Gaussian with standard deviation σ and gradient operator ∇ . The termination energy is obtained from

curvature of contour's level $C(x, y)$. Each control point can be updated using gradient-descent method iteratively:

$$\vec{x}_t = (A - \gamma I)^{-1} (\gamma \vec{x}_{t-1} - \vec{h}_x(\vec{x}_{t-1}, \vec{y}_{t-1})) \quad (7a)$$

$$\vec{y}_t = (A - \gamma I)^{-1} (\gamma \vec{y}_{t-1} - \vec{h}_y(\vec{x}_{t-1}, \vec{y}_{t-1})) \quad (7b)$$

A is pentadiagonal matrix which contains the numerical coefficients to descent internal energy gradient [12]. In fact, this model is problematic because the snake behavior depends heavily on the energy weights [1].

The performance of this active contour model can be improved by metaheuristic optimization framework such as particle swarm optimization which is described in the next section.

Particle Swarm Optimization

Metaheuristic approaches are often useful for complex problems by producing nearly optimum results where exact solution is not achievable. Particle Swarm Optimization as one member in this family has proven to be effective and efficient. Since PSO was introduced by Kennedy and Eberhart in 1995 [13], it has been received a lot of attentions from researchers [14].

The social behavior of animals that is moving together toward foods inspires researchers to the idea of PSO algorithms. It is interesting to simulate the dynamics of swarm's movement based on their momentum, cognitive and social interactions. In D -dimensional search-space, the actual positions can be denoted as $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. Any particle that achieves better position, which noticed as p_b , influences the neighbors to attract them together to the optimal solution. In addition, each particle is also directed by its best previous positions p_i . The particles update their positions based on mechanics formula.

$$v_{id}(t+1) = wv_{id}(t) + c_1r_1(p_{id}(t) - x_{id}(t)) + c_2r_2(p_{bd}(t) - x_{id}(t)) \quad (8a)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (8b)$$

where

- d is d -th dimension in the parameter space;
- x_{id} is position of i -th particle;
- v_{id} is velocity of i -th particle;
- c_1 and c_2 are cognitive and social acceleration learning rate;
- r_1 and r_2 are random numbers between 0 and 1 with uniform distribution;
- w is inertia weight to balance the local and global searches [15].

In this research, the objective function is defined from the external energy (Eq. (3)). The best weights are obtained by:

$$\min w = \arg \min_w F(w), \quad w_i \in [0, 1], \quad i \in \{1, 2, \dots, n\} \quad (9)$$

$$F(w) = \sum_{i=1}^n w_i E_i, \quad w \in [0, 1] \quad (10)$$

where n is set as 3 according to line, edge and terminate energy functions in Eq. (3). Typically, the iteration is terminated when external energy becomes stable. The pseudocode of the energy minimization is given as follows:

1. Set initial population w of weight parameters w_i which is assigned with random position and velocity
2. Evaluate objective function $F(w)$ for each weight candidate and find the best w_i , $i = 1, \dots, n$.
3. Update the velocity for each candidate solution and swarm.
4. Update the position for each candidate solution and swarm.
5. Repeat step 2 to 4 until stopping condition is achieved.

Note that most of images are corrupted of noises. It is necessary to filter the original image before the above algorithm is performed. As it is seen in the pseudocode, the weight parameters for external energy can be determined automatically using PSO algorithm.

Results and discussions

The proposed algorithm was implemented on Core 2 Duo 2.33 GHz, 3GB RAM. The basic code of snake's algorithm can be found on Ritwik Kumar homepage [16]. The experiments was performed on four standard images. The first two images are biomedical image i.e. heart and chest. The other test images are vase and U64. For each test image, the active contour model parameters have the same values ($\alpha = 0.4$, $\beta = 0.2$, $\gamma = 1$). At first, each image is filtered using Gaussian function with standard deviation $\sigma = 3$. The particle swarm parameters are set as follows:

- population = 20; maximum velocity = 1; minimum velocity = 0;
- cognitive rate = social rate = 1.4; maximum generation = 50.

The results of estimated weights parameter are given in Table 1.

Table 1. The weights values between traditional and proposed methods

Image	Traditional			Proposed		
	w_{line}	w_{edge}	w_{term}	w_{line}	w_{edge}	w_{term}
Heart	0.10	0.70	0.20	0.81	0.70	0.75
Chest	-0.20	0.70	0.70	0.41	0.22	0.50
Vase	0.30	0.40	0.70	0.10	0.88	0.78
U64	0.10	0.70	0.70	0.30	0.29	0.55

The results showed that the PSO algorithm produced different values of weights combination. Heart image has largest value at w_{line} . The Chest and U64 images have the largest value at

w_{term} . The Vase image has largest value at w_{edge} . In contrast to traditional method, most images have largest values at w_{edge} . In fact, the determination of the traditional methods require lots of experiences from the users which are impractical and troublesome. The accuracy evaluation is shown in Fig. 1 and Fig. 2.

The initial control points for both traditional and proposed method is shown in Fig. 1(a). The Heart image was tested using 200 iterations and 11 control points. As it is shown in Fig. 1(b), the traditional method failed to fit the object boundaries. On the other hand, the proposed method showed more accurate result. The Chest image was tested using 300 iterations and 18 control points. The traditional method also failed to detect the object boundaries at the lower part. A better accuracy was achieved by the proposed method with smaller error.

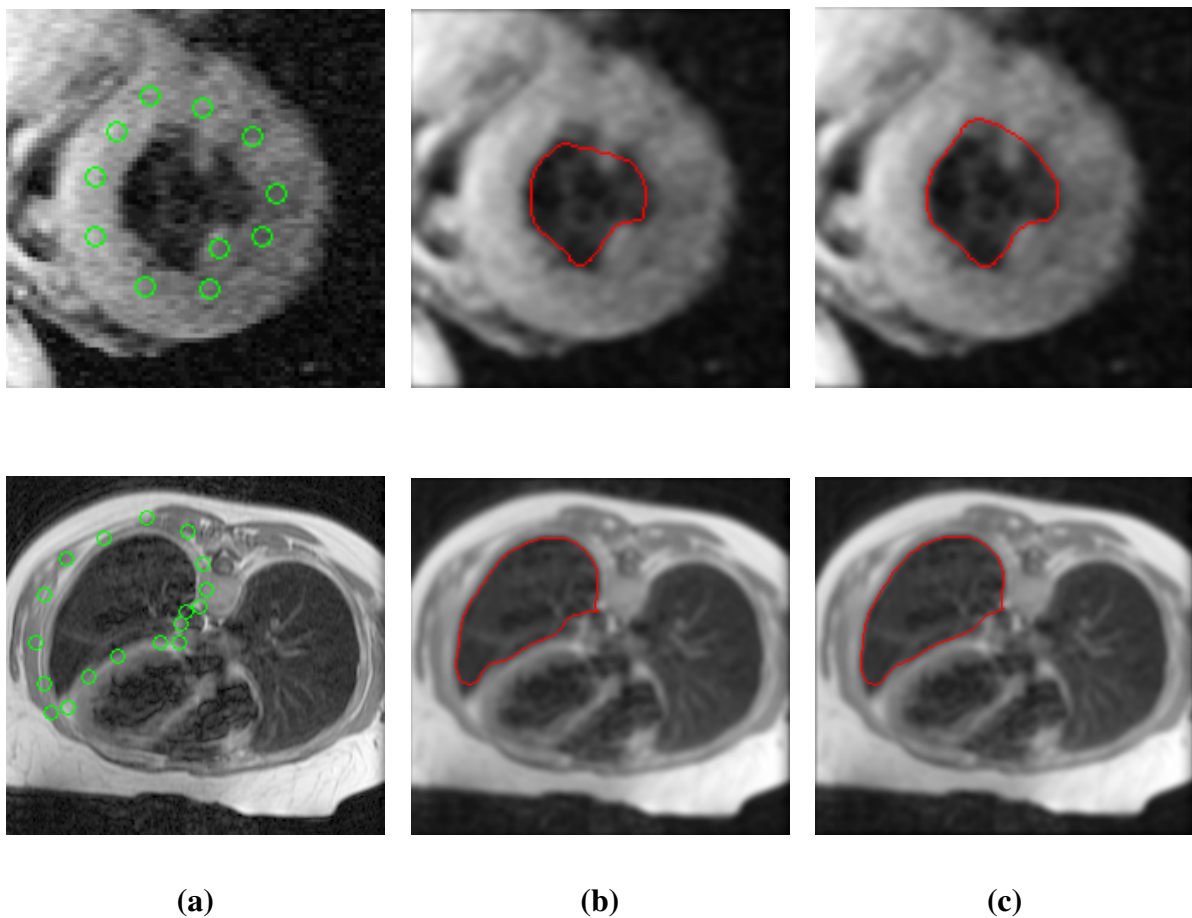


Fig. 1 Heart (top) and Chest (bottom):
(a) Initial control points (b) Traditional method (c) Proposed method

The results for non biomedical images are shown in Fig. 2. This experiment was aimed to show the generalization property of the proposed method. The initial control points for both traditional and proposed method are shown in Fig. 2(a). The Vase image was tested using 300 iterations and 19 control points. As shown in Fig. 1(b), the traditional method failed to fit the vase boundaries at the left side. On the other hand, the proposed method showed more accurate result. Notice that more iteration on traditional method can produce better accuracy. However, more iterations consumes higher computational time which is not desirable. This means the use of PSO did not only improve the accuracy but also the effectiveness of traditional

snake algorithm. The U64 image was tested using 400 iterations and 21 control points. The traditional method also failed to detect the object boundaries at lower part. This means more iteration and time are required to achieve more accurate result. On the other hand, the proposed method achieved accurate result with same iteration.

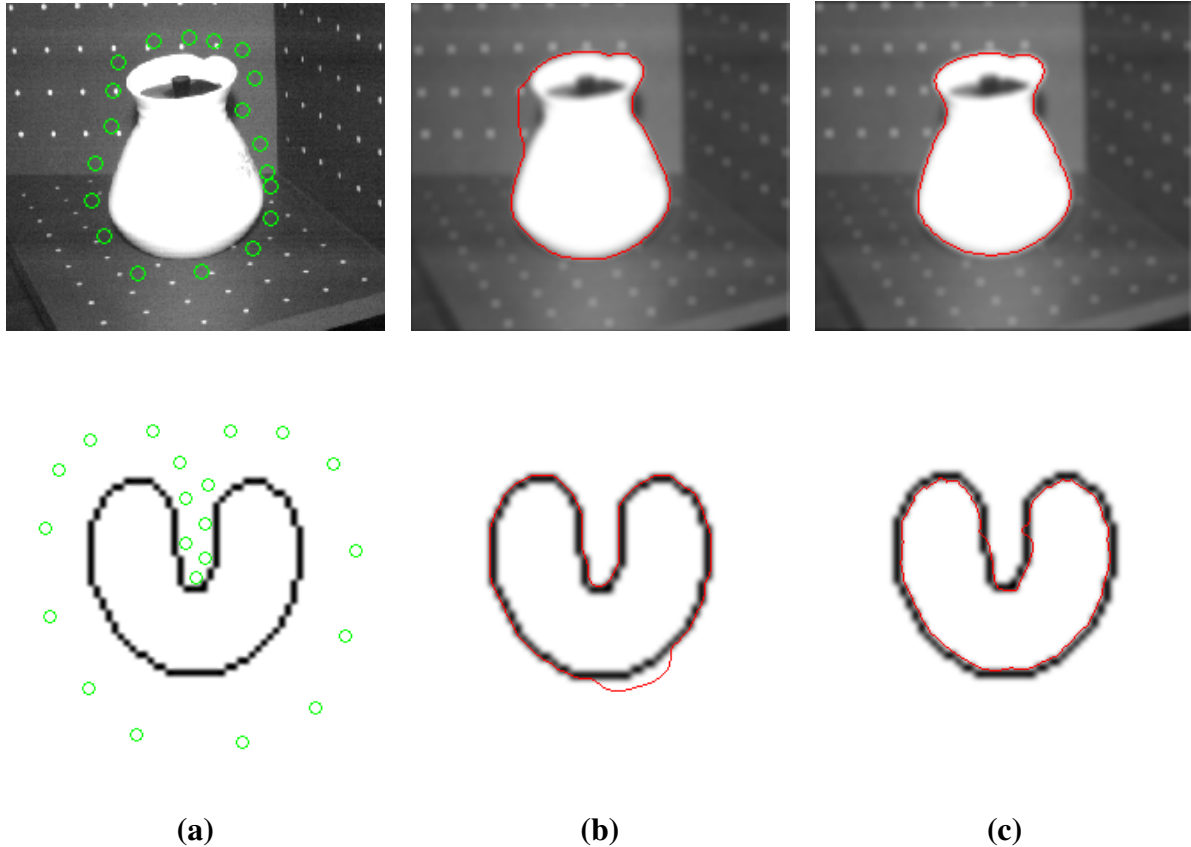


Fig. 2 Vase (top) and U64 (bottom):
(a) Initial control points (b) Traditional method (c) Proposed method

Conclusion

This research proposed a hybrid active contour model and PSO algorithm. It has been validated that different weighted combination of image energy functions can produce totally different B-Spline snake behaviors. In contrast to traditional method which requires the user to find the optimum combination manually, the proposed algorithm offers semi automatic method for medical image segmentation. This method enables the snake to initialize the image energy coefficient automatically and in more convenient way. The experimental results on biomedical images demonstrated that the proposed method can improve the snake behavior and superior to manual weights parameter determination. The experiments on non biomedical images were also performed. The results also demonstrate that the proposed method was able to fit the object boundaries more accurately and faster. However, this method requires the users to select proper initial control points and the other active contour model parameters such as tension and rigidity coefficients. In future, automatic control points initialization has to be included into snake models. Other studies are also suggested to explore the capabilities of metaheuristic methods to estimate the other active contour model parameters.

Acknowledgements

The authors thank to Universiti Teknikal Malaysia Melaka for the fund support of the Zamalah Scheme.

References

1. Kass M., A. Witkin, D. Terzopoulos (1988). Snakes: Active Contour Models, *Int. J. Comp. Vision*, 1(4), 321-331.
2. McInerney T., D. Terzopoulos (1996). Deformable Models in Medical Image Analysis, *Proc. IEEE Workshop on Mathematical Methods in Biomedical Image Analysis*, 171-180.
3. Kang D. J. (1999). A Fast and Stable Snake Algorithm for Medical Images, *Pattern Recognition Letters*, 20, 507-512.
4. Lam C. L., S. Y. Yuen (1998). An Unbiased Active Contour Algorithm for Object Tracking, *Pattern Recognition Letters*, 19, 491-498.
5. Williams D. J., M. Shah (1992). A Fast Algorithm for Active Contours and Curvature Estimation, *CVGIP: Image Understanding*, 55(1), 14-26.
6. Li C., J. Liu, M. D. Fox (2005). Segmentation of External Force Field for Automatic Initialization and Splitting of Snakes, *Pattern recognition*, 38(11), 1947-1960.
7. Xu C., J. L. Prince (1998). Generalized Gradient Vector Flow External Force for Active Contours, *Signal Processing*, 71(2), 131-139.
8. Xu C., J. L. Prince (1998). Snakes, Shapes, and Gradient Vector Flow, *IEEE Transactions on Image Processing*, 7(3), 359-369.
9. Heckel F., O. Konrad, H. K. Hahn, H. Peitgen (2011). Interactive 3D Medical Image Segmentation with Energy-minimizing Implicit Functions, *Computers and Graphics*, 35(2), 275-287.
10. Tseng C. C., J. G. Hsieh, J. H. Jeng (2009). Active Contour Model via Multi-population Particle Swarm Optimization, *Expert Systems with Applications*, 36(3), 5348-5352.
11. Horng M., R. Liou, J. Wu (2010). Parametric Active Contour Model by using the Honey Bee Mating Optimization, *Expert Systems with Applications*, 37(10), 7015-7025.
12. Park H., T. Schoepflin, T., Y. Kim (2001). Active Contour Model with Gradient Directional Information: Directional Snake, *IEEE Transactions on Circuits and System for Video Technology*, 11(2), 252-256.
13. Kennedy J., R. Eberhart (1995). Particle Swarm Optimization, *Proc. IEEE International Conference on Neural Networks*, 4, 1942-1948.
14. Eberhart R. C., Y. Shi (2004). Guest Editorial Special Issue on Particle Swarm Optimization, *IEEE Transaction on Evolutionary Computation*, 8(3), 201-228.
15. Shi Y., R. Eberhart (1998). A Modified Particle Swarm Optimizer, *Proc. IEEE International Conference on Evolutionary Computation*, 69-73.
16. <http://people.seas.harvard.edu/~rkkumar/>

Habibullah Akbar, M.Sc.

E-mail: habibrown@gmail.com



He received the Bachelor of Science in Physics at Institut Teknologi Bandung (ITB) in 2006. He received Master of Science in Information and Communication Technology (ICT) at Universiti Teknikal Malaysia Melaka (UTeM) in 2010. His research interests include computer vision, robotics, and electronics

Prof. Nanna Suryana, Ph.D.

E-mail: nsuryana@utem.edu.my



Professor Dr. Nanna Suryana has received his B.Sc. in Soil and Water Eng. (Bandung, Indonesia), M.Sc. in Comp. Assisted for Geoinformatics and Earth Science, (Enschede, Holland), Ph.D. in Geographic Information System (GIS) (Wageningen, Holland). He is currently holding a position of Director of International Office and lecturer at Faculty of Information Technology and Communication (FTMK) of Universiti Teknikal Malaysia Melaka (UTEM). His current research interest is in field of GIS and Data Mining.

Prof. Shahrin Sahib, Ph.D.

E-mail: shahrinsahib@utem.edu.my



He received the Bachelor of Science in Engineering, Computer Systems and Master of Science in Engineering, System Software in Purdue University in 1989 and 1991 respectively. He received the Doctor of Philosophy, Parallel Processing from University of Sheffield in 1995. He is a professor and Dean of Faculty of Information Technology and Communication at the Universiti Teknikal Malaysia Melaka. His research interests include network security, computer system security, network administration and network design. He is a member panel of Experts National ICT Security and Emergency Response Center and also Member of Technical Working Group: Policy and Implementation Plan, National Open Source Policy.