SNAKES FOR OBJECT CONTOUR TRACKING IN STEREO SEQUENCES

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ABSTRACT

In this paper, we propose a snake algorithm for tracking contours of object in stereo sequences with cluttered background. Our newly designed algorithm is developed by using disparity information taken from stereo image sequence. The proposed algorithm can successfully extract the concave contour of an object and track the contour in a complex image. Performance of the proposed algorithm has been verified by simulation.

1. INTRODUCTION

Various object tracking schemes for object extraction from 2D images have been developed over the last two decades. Related literatures can be found in [1-5]. However, a major problem with 2D object tracking methods is that their performance decreases rapidly especially when the background is cluttered.

Recently, significant attention has been given to stereo image based object tracking and understanding for stereoscopic systems, video surveillance, and robotics [6-7]. Conventional object tracking methods using disparity information have the advantage of separating the background from the object of interest (*OOI*). Nevertheless, most of these methods are in fact tracking the area or position of the *OOI* rather than the object contour.

The recent development in object contour tracking using an active contour model known as snakes is the focus of our investigation. Snakes are very effective in extracting and tracking object contours. However, snakes have a difficulty progressing into concave boundary regions, and easily get stuck in local minima.

In this paper, we propose a snake algorithm for object contour tracking that can overcome the limitations found in cluttered background and concave boundary regions. A newly designed energy function is defined in the disparity space.

This paper is organized as follows. Section 2 covers the fundamentals in snake algorithms. Our newly designed snake algorithm is presented in Section 3. In Section 4, the simulation for evaluating the performance of our method is presented, and the conclusions are given in Section 5.

2. FUNDAMENTALS OF SNAKE ALGORITHM

The snake algorithm was first introduced by Kass et al. [4]. A snake is the energy-minimizing spline guided by internal constraint forces and influenced by external image forces that pull it toward features such as lines and edges. In the discrete formulation of a snake, the contour is represented as a set of snake points $v_i = (x_i, y_i)$ for $i = 0,...,M-1$ where x_i and y_i are the x and y coordinates of a snake point, respectively and M is the total number of snake points. Then the typical form of the energy function for the snakes can be written as follows:

$$E_{snake}(v) = \sum_{i=0}^{M-1}\left(E_{\text{int}}(v_i) + E_{\text{ext}}(v_i)\right) \tag{1}$$

It contains two energy components. The first component is called an internal energy concerning properties such as bending or discontinuity of a contour. The second component is the external energy that defines the gradient of the image at a snake point.

The current tracking method of the snake algorithm has been applied to 2D single image sequences by simply combining motion compensation error (MCE) with the snake energy function to track the *OOI* [3]. However, snake points can converge into local minima in the case of a cluttered background.

3. PROPOSED SNAKE ALGORITHM FOR OBJECT CONTOUR TRACKING

In this section, we describe our new snake energy function defined in disparity space. Consider the 3D disparity space defined by x, y, and a disparity axis d [8]. The stereo image description in the disparity space is illustrated in Fig. 1. The figure contains the left and the right stereo images, i.e., $f_l(x, y)$ and $f_r(x, y)$; the 2D disparity map $f_{DM}(x, y)$ obtained by using the disparity information, which is estimated by using stereo matching; and the illustration of separated objects A, B, and C defined in 3D disparity space. In the disparity space the snake point is defined as $v_{i,t}^d = (x_{i,t}, y_{i,t}, d_{i,t})$ at frame t. In our algorithm, we do not use the MCE for motion estimation. We assume that the *OOI* does not have a large motion, rotation, or deformation.

3.1 Internal energy functions

3.1.1 Continuity energy function

The first term of internal energy function is the continuity energy and its definition is as follows:

$$E_{con}(v_{i,t}^d) = \frac{\left|\overline{D_t^d} - \left\|v_{i,t}^d - v_{i-1,t}^d\right\|\right|}{\overline{D_t^d}} \tag{2}$$

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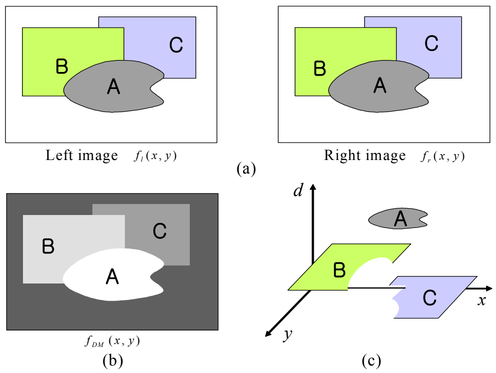

Fig. 1. Image description in disparity space: (a) Stereo images (left image $f_l(x,y)$, right image $f_r(x,y)$); (b) Disparity map $f_{DM}(x,y)$ (c) Objects in disparity space.

$$\overline{D_t^d} = \frac{1}{M}\sum_{i=0}^{M-1}\left\| v_{i+1,t}^d - v_{i,t}^d \right\| \tag{3}$$

The main role of the continuity energy term is to make even spacing between the snake points by minimizing the difference between $\overline{D_t^d}$ and $\left\| v_{i,t}^d - v_{i-1,t}^d \right\|$, where $\overline{D_t^d}$ is the average distance between neighboring snake points.

3.1.2 Curvature energy function

The curvature energy encourages a smooth curvature formation involving current, previous, and next snake points. Usually, the initial snake points are set at the outside of the object and shrink inwards. Otherwise, they are set at the inside of the object and dilate. We must determine the moving direction of snake points as shown in Fig. 2 based on whether the position of snake points is outside or inside the *OOI*. As shown in Fig. 2, a snake point is associated with three vectors (Frenet formulas): tangent vector T , normal vector $N = T^{'}/\left\|T^{'}\right\|$, and binormal vector $B = T \times N$. Where $\|T'\|$ is the length of the curvature vector, and the sign of B can be set positive If B is upward or set negative if it is downward. In the case that a snake point is in the inside of the *OOI* (as in Fig. 2(a) and 2(b)), the movement of the snake points can be described as follows:

i) In Fig. 2(a), the snake point $v_{i,t}^d$ must take the direction of the dotted arrow in order to converge on the boundary of the *OOI*. Therefore, because B is upward, $v_{i,t}^d$ must move along the direction of N to reach a point that minimizes the value of curvature $\|T'\|$.

ii) In case of Fig. 2(b), the dotted arrow is in the opposite direction of N. Here, B is downward and $v_{i,t}^d$ moves in the opposite direction of N seeking a point with maximum value of $\|T'\|$.

If the snake point is at the outside of the *OOI*, we simply apply the contrary. Therefore, we can make the snake points move to the boundary of the *OOI* regardless of their position, and we can solve the problem which occurs with concave regions as shown in Fig. 2(c). T, N, and B are defined as follows:

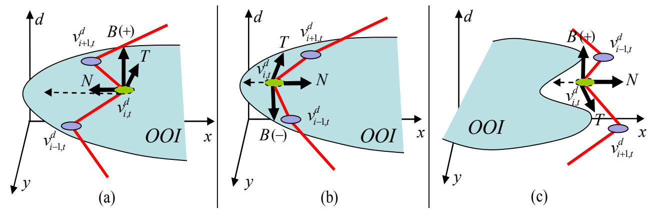

Fig. 2. Binormal vector based curvature energy.

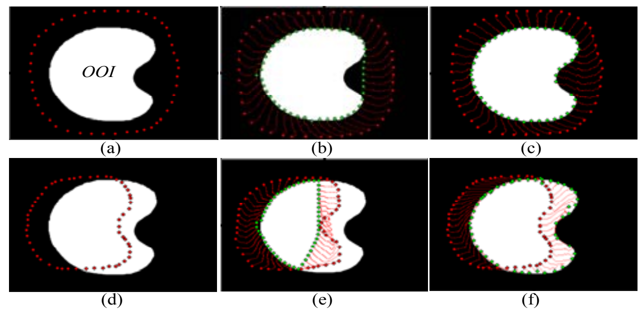

Fig. 3. Comparison of the conventional curvature energy with the proposed curvature energy.

$$T(v_{i,t}^d) = v_{i+1,t}^d - v_{i,t}^d \tag{4}$$
$$N(v_{i,t}^d) = v_{i-1,t}^d - 2v_{i,t}^d + v_{i+1,t}^d \tag{5}$$
$$B(v_{i,t}^d) = T(v_{i,t}^d) \times N(v_{i,t}^d) \tag{6}$$

The normalized curvature energy is defined as Eq. (7) [5]. The proposed total curvature energy $E_C(v_{i,t}^d)$ is presented as Eq. (8).

$$E_{cur}(v_{i,t}^d) = \left\| \, T(v_{i,t}^d)/\left\|T(v_{i,t}^d)\right\| - T(v_{i-1,t}^d)/\left\|T(v_{i-1,t}^d)\right\| \, \right\| \tag{7}$$
$$E_C(v_{i,t}^d) = \beta(\lambda E_{cur}(v_{i,t}^d) + (\lambda - 1)E_{cur}(v_{i,t}^d)) \tag{8}$$

λ is set to 1 if the snake point is at the inside of the object and to 0 otherwise. The constant β can be set for different applications, depending on the direction of $B(v_{i,t}^d)$ on the contour. In case that λ is set to 1, β carries the same sign as $B(v_{i,t}^d)$. Otherwise, β carries the opposite sign of $B(v_{i,t}^d)$ in Eq. (8) when λ is set 0.

In order to demonstrate the performance of the proposed curvature energy, the simulation results for concave object are illustrated in Fig. 3. Fig. 3(a) and (d) show initial snake points. The results for the conventional curvature energy are shown in Fig. 3(b) and (e). Fig. 3(c) and (f) show the result for proposed curvature energy. Our proposed method has successfully converged onto the boundary of the *OOI* in both cases, while the conventional method has failed to converge onto the concave boundary of the *OOI* in either case.

3.2 External energy functions

In the conventional method, external energy computation involves edge information taken from a single image. However, when *OOI* gets influenced by a cluttered background, the behavior of external energy computation changes and negative effects begin to occur. In order to maintain the role of external energy and to enhance the tracking performance of our algorithm, we propose a better energy function.

In this paper, stereo images were acquired using two cameras arranged in parallel. Vertical disparities are all zeros, and horizontal disparities are defined as the difference between the column coordinates of the pixel locations of corresponding pixels in the left and right images of a stereo image. We use a layer image to get the disparity of the *OOI* for the external energy in disparity space. Disparity map is obtained by segments-based stereo matching [9]. Segments-based stereo matching has the advantage that it preserves the object's boundary and prevents the fattening effect.

Mapping of the disparity map $f_{DM}(x,y)$ onto the disparity space is performed by using the $f_{DM}(x,y)$, and as a result $f_{DS}(x,y,d)$ is created in the disparity space as follows:

$$f_{DS}(x,y,d)=\begin{cases} f_{DM}(x,y) & d=f_{DM}(x,y) \\ 0 & d\neq f_{DM}(x,y)\end{cases} \tag{9}$$

The external energy in disparity space is illustrated in Fig. 4. We now can define a new normalized external energy as follows:

$$E_{ext}(v_{i,t}^{d})=-\frac{\left|\nabla f_{DS}(x_{i,t},y_{i,t},d_{OOI,t})\right|}{e_{\max}} \tag{10}$$

Where $f_{DS}(x_{i,t},y_{i,t},d_{OOI,t})$ is a layer image with a disparity value of the *OOI* as in Fig. 4(d). $e_{\max}$ is maximum value in neighborhood.

3.3 Proposed new snake energy function

The proposed snake energy function for object contour tracking is defined as follows:

$$E_{tracking}(v_t^d)=\sum_{i=0}^{M-1}\Big(\alpha E_{con}(v_{i,t}^d)+\beta(\lambda E_{cur}(v_{i,t}^d) + (\lambda-1)E_{cur}(v_{i,t}^d))+\gamma E_{ext}(v_{i,t}^d)\Big) \tag{11}$$

The parameters α, β, and γ are selected to balance the relative influence of the three terms.

4. EXPERIMENTAL RESULTS

In order to verify the performance of our snake algorithm utilizing disparity information taken from a pair of stereo images, a set of experiments using computer simulation has been performed. The algorithm is coded in Visual C++ 6.0, and the simulation was performed on a Pentium IV machine with 512 MB of memory running at 2 GHz clock speed. We used real stereo image sequences taken by two USB cameras separated at 4 cm from each other along the baseline. Image size is 320×240.

To quantify the segmentation performance of our snake algorithm and then compare it to the conventional snake algorithm [3], a performance measure in terms of root mean square error (RMSE) is defined as follows:

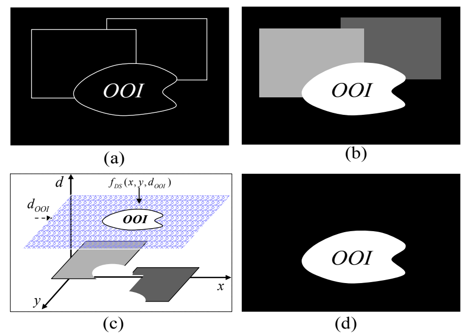

Fig. 4. External energy in disparity space: (a) segmented image, (b) disparity map $f_{DM}(x,y)$ obtained using segments-based stereo matching, (c) $f_{DS}(x,y,d)$: Mapping of $f_{DM}(x,y)$ onto a disparity space, and (d) $f_{DS}(x,y,d_{OOI})$: layer image obtained by disparity of *OOI* in disparity space.

$$RMSE(t)=\sqrt{\frac{\sum_{i=0}^{M-1}\left\|v_{i,t}^{f}-o_{i,t}\right\|^2}{M}} \tag{12}$$

Where $v_{i,t}^{f}$ is a snake point at the end of iterations in frame t; $o_{i,t}$ is the true position of object boundary. The smaller the *RMSE* value, the more the snake points have converged well to the boundary of the *OOI*.

The simulation process and its results are illustrated in Fig. 5 and Fig. 6, and the performance comparison in terms of *RMSE* is summarized in Fig. 7.

Results of the proposed function for external energy are shown in Fig. 5. The *OOI* is that taken in the person's hand. The left image is shown in Fig. 5(a), and the edge obtained using the Sobel operator in the left image is shown in Fig. 5(b). The image has a complex background and noise. Fig. 5(c) shows the disparity map obtained using the sum of squared difference (SSD). Matching error and fattening effect made the boundary of the *OOI* loose, (matching window size 5×5). Fig. 5(d) shows the disparity map obtained using segment-based stereo matching. A layer image $f_{DS}(x,y,d_{OOI})$ that separated the *OOI* region from background is shown in Fig. 5(e). Therefore, we can certify that the boundary of *OOI* is extracted.

The simulation results of our proposed algorithm in comparison with the conventional algorithm are illustrated in Fig. 6. The number of snake points is 30, and the initial points were placed manually. Noticeably, the conventional algorithm could not track the boundary of *OOI* as shown in Fig. 6 (a) due to the adverse effects of the neighboring objects and edges. In frame 8 and 12, snake points could not converge into the concave boundary of the *OOI*. However, our proposed algorithm showed a highly satisfactory tracking of the boundary of the *OOI* as shown in Fig. 6 (b).

Fig. 7 illustrates the performance of our algorithm compared to the conventional algorithm in terms of *RMSE* for the experiment performed above. For our algorithm, the snake points migrated successfully toward the true boundary of the *OOI* in the experiment, and, correspondingly, the values of *RMSE* are kept relatively small.

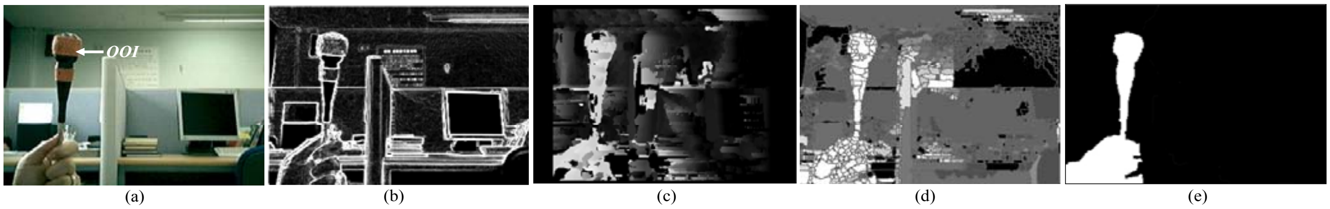

Fig. 5. Illustration of the layer image $f_{DS}(x, y, d_{OOI})$

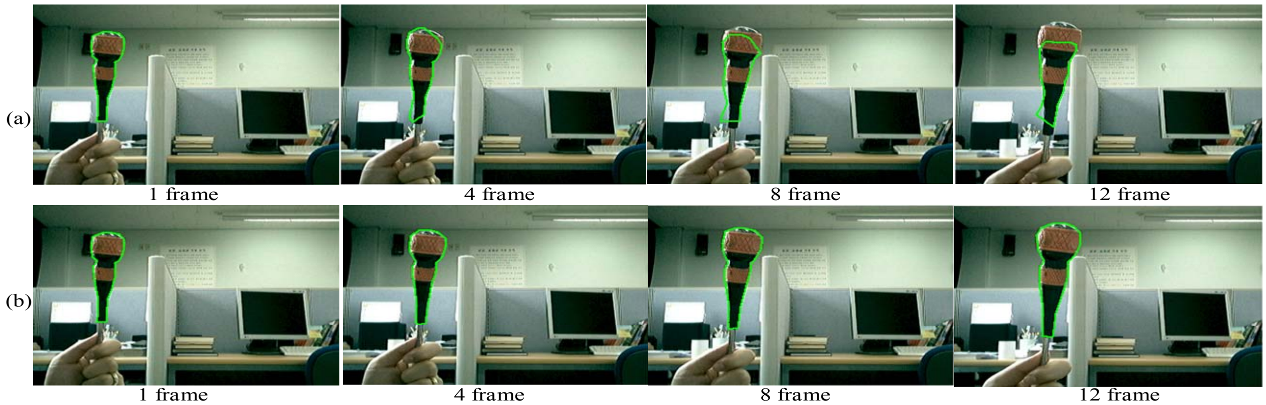

Fig. 6. The results of experiment: (a) conventional algorithm, (b) the proposed algorithm

5. CONCLUSIONS

In this paper, we propose a snake algorithm for object contour tracking in stereo sequences. Our newly defined energy function in the disparity space is a major factor for our algorithm to achieve successful object contour tracking even on a cluttered background and with concave boundary regions. Our algorithm could successfully eliminate a cluttered background using disparity information. Movement of snake points in concave boundary regions is determined using disparity information and the binormal vector. Therefore, we can solve the problem which occurs with concave boundary of *OOI*, and can prevent the snake from getting stuck in local minima. A comprehensive set of experiments to verify the performance of our snake algorithm using computer simulation has shown us an excellent object contour tracking capability enhancement over those of conventional method. However, our algorithm increases the computational cost for involving stereo images. In order to be applicable to a real-time object-based 3D system, our algorithm needs to be followed by a further study to explore ways to reduce processing time.

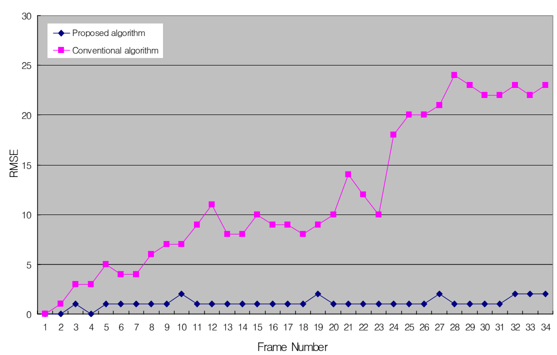

Fig. 7. $RMSE$ change in experiment

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