# Texture Segmentation Using Active Contour Model with Edge Flow Vector

T. Boonnuk, S. Srisuk, and T. Sripramong

***Abstract*—We present a novel technique using active contour model (ACM) incorporating with edge flow for texture segmentation. The edge flow magnitude was used as an external force of active contour model. The active contour model will be guided by the edge flow vector. In our method, the gradient vector flow was replaced by the edge flow vector. Using edge flow vector, texture image can be segmented efficiently. The results of texture segmentation using active contour model with edge flow vector and gradient vector flow will be compared. It was observed that the active contour model with edge flow vector shown better texture segmentation capability. It should be pointed out that the texture image cannot be segmented using the traditional ACM and gradient vector flow. We also found that it is suitable to be applied in the MRI image segmentation.**

***Index Terms*—Texture segmentation, active contour model, gradient vector flow, edge flow vector.**

## I. Introduction

At present, image segmentation has been widely used in various application such as identification of objects in satellite image for geographic information system [1], visual inspection for finding physical defects (e.g. contaminations, crack, etc.) in manufacturing [2], identify tumor from medical imaging [3].

Image segmentation is part of image processing technique which is used to partition image into multiple segments in order to simplify initial image for further analysis.

Several methods can be used for image segmentation. The thresholding method divides image using threshold value, the edge detection method identifies edge or region boundary, and some techniques use color, gray scale or texture to segment image e.g. edge flow technique [4].

Edge flow technique is a powerful method for texture segmentation. It can be used to segment texture image which has non-uniform gray scale. It is known that the thresholding technique and edge detection cannot be used to segment texture from initial image [5].

In 1978, technique such as active contour model was proposed by Kass et.al. [6]. Later the active contour model was developed in 2 ways. First, edge-based active contour which uses edge as an external force to move contour. Xu and Prince [7] used gradient vector flow as external force, an example for edge-based active contour. The alternative way is region-based active contour that uses region as an external force to move contour. Chan and Vese [8] used level set method for image segmentation.

In Section II, we describe a method for texture segmentation including traditional active contour model, edge flow method and active contour model with gradient vector flow. We introduce a new algorithm for texture segmentation using active contour model with edge flow vector in Section II-D. We compare the results of several methods in Section III. We give a discussion in Section IV. In Section V, the conclusion is provided.

## II. Methodology

### A. Traditional Active Contour Model

In 1987, Kass *et al*. [6] proposed active contour model for image segmentation, called Snake. This technique requires initial contour as a starting contour for image segmentation. The shape of contour is changed and moved toward the boundary of the objects in an image. The equation of moving contour usually derived from numerical method. For traditional active contour model, the curve $x(s) = [x(s), y(s)]$ that $s \in [0, 1]$ was moved in spatial domain of image to minimize the Snake energy functional:

$$E_{snake} = \int_0^1 \frac{1}{2}[\alpha|x'(s)|^2 + \beta|x''(s)|^2] + E_{ext}(x(s))ds \tag{1}$$

where $\alpha$ and $\beta$ is weighting parameter controlling contour smoothing while contour is moving. The $x'$ and $x''$ are first and second order derivative of contour and $E_{ext}$ is external energy obtained from the image.

Typically, the external energy ($E_{ext}$) is defined to move contour close to the image features. The equation of external energy is shown as follow:

$$E_{ext}(x, y) = -|\nabla[G_\sigma(x, y) \times I(x, y)]|^2 \tag{2}$$

where $G_\sigma(x, y)$ is a two dimension Gaussian function consisting of standard deviation ($\sigma$) and gradient operator ($\nabla$). In case the image is a black line on white background, a suitable external energy are

$$E_{ext}(x, y) = G_\sigma(x, y) \times I(x, y) \tag{3}$$

To increase the capture range of active contour a large $\sigma$'s are often necessary. The snake that minimizes energy is typically obeyed with the Euler equation:

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T. Boonnuk and T. Sripramong are with The Electrical Engineering Graduate Program, Faculty of Engineering, Mahanakorn University of Technology, Bangkok, Thailand (e-mail: boonnuk2002@hotmail.com, thanwa@mut.ac.th).

S. Srisuk is with Faculty of Industrial Technology, Nakhon Phanom University, Nakhon Phanom, Thailand (e-mail: srisuk.s@gmail.com).

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$$\alpha x''(s) - \beta x''''(s) - \nabla E_{ext} = 0 \tag{4}$$

It can be viewed as force balance equation:

$$F_{\text{int}} + F_{ext} = 0 \tag{5}$$

where $F_{\text{int}} = \alpha x''(s) - \beta x''''(s)$ and $F_{ext} = -\nabla E_{ext}$ . The internal force $F_{\text{int}}$ is used to control smoothing of contour while external force $F_{ext}$ change a shape and move contour closer to the edge of object.

To solve equation (4) Snake is made to be dynamic that defined $x$ as function of time. The dynamic snake equation is shown as:

$$X_t(s,t) = \alpha x''(s,t) - \beta x''''(s,t) - \nabla E_{ext} \tag{6}$$

### *B. Edge Flow Method*

Edge flow is a new technique for boundary detection that requires very little parameter tuning. Traditionally edges are located at the local maxima of the gradient in the intensity/image feature space. In contrast, the detection and localization of edges (or image boundaries in a more general sense) are performed indirectly in the proposed edge flow method: first by identifying a flow direction at each pixel location that points to the closest boundary; then followed by the detection of locations that encounter two opposite directions of edge flow. Edge flow direction was shown in Fig. 1.

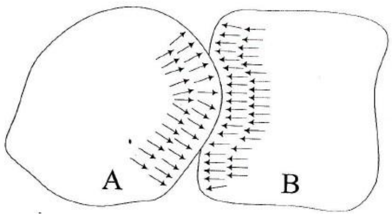


Fig. 1. Edge flow direction.

Since any of the image attributes such as color, texture, or their combination can be used to compute the edge energy and direction of flow, this scheme provides a general framework for integrating different image features for boundary detection.

The edge flow method utilizes a predictive coding model to identify and integrate the direction of change in image attributes such as color, texture, and phase discontinuities, at each image location. Towards this objective, the following values are computed: $E(s, \theta)$ which measures the edge energy at pixel s along the orientation $\theta$, $P(s, \theta)$ which is the probability of finding an edge in the direction of $\theta$ from $s$, and $P(s, \theta+\pi)$ which is the probability of finding an edge along $\theta+\pi$ from $s$. These edge energies and the associated probabilities can be computed in any image feature space of interest, such as color or texture and can be combined by equations (10) to (13). From these measurements, an edge flow vector $\vec{F}_{(s)}$ is then computed. The magnitude of $\vec{F}_{(s)}$ represent the total edge energy and $\vec{F}_{(s)}$ points in the direction of finding the closest boundary pixel.

Computing $E(s, \theta)$: Now consider an image at a given scale $\sigma$ as $I_\sigma(x, y)$, which is obtained by smoothing the original image $I(x, y)$ with a Gaussian kernel $G_\sigma(x, y)$. The scale parameter controls both the edge energy computation and the local flow direction estimation, so that only edges larger than the specified scale are detected. The edge energy $E(s, \theta)$ at scale $\sigma$ is defined to be the magnitude of the gradient of the smoothed image $I_\sigma(x, y)$, which is obtained by smoothing the original image $I(x, y)$ with a Gaussian kernel $G_\sigma(x, y)$. The scale parameter along the orientation $\theta$

$$\begin{aligned} E(s,\theta) &= \left| I(x,y) \times \frac{\partial}{\partial n} G_\sigma(x,y) \right| \\ &= \left| I(x,y) \times GD_{\sigma,\theta}(x,y) \right| \end{aligned} \tag{7}$$

This edge energy indicates the strength of the intensity change. Many existing edge detectors actually use similar operations to identify the local maxima of intensity changes as edges.

Computing $P(s, \theta)$: For the edge energy $E(s, \theta)$, there are two possible flow directions: the forward ($\theta$) and the backward ($\theta+\pi$). The likelihood of finding the nearest boundary along these two directions is now estimated. Consider the use of image intensity at location $s$ to predict its neighbor in the direction $\theta$. The error in prediction is defined to be

$$\begin{aligned} Error(s,\theta) &= \left| I_\sigma(x + d\cos\theta, y + d\sin\theta) - I_\sigma(x,y) \right| \\ &= \left| I(x,y) \times DOOG_{\sigma,\theta}(x,y) \right| \end{aligned} \tag{8}$$

where $d$ is the offset distance in the prediction, and is proportional to the scale at which the image is being analyzed. A large prediction error in a certain direction implies a higher probability of finding a boundary in that direction. Therefore, the probabilities of edge flow direction are assigned in proportion to their corresponding prediction errors

$$P(s,\theta) = \frac{Error(s,\theta)}{Error(s,\theta) + Error(s,\theta+\pi)} \tag{9}$$

The edge energies and the corresponding probabilities obtained from different image attributes can be combined together to form a single edge flow field for boundary detection. The total of edge energies and probabilities of edge flow direction are defined as

$$E(s,\theta) = \sum\nolimits_{a\in A} E_a(s,\theta).w(a) \text{ and } \sum\nolimits_{a\in A} w(a) = 1 \tag{10}$$

$$P(s,\theta) = \sum_{a\in A} P_a(s,\theta).w(a) \tag{11}$$

where $E_a$ $(s,\theta)$ and $P_a$ $(s,\theta)$ represent the energy and probability of the edge flow computed from image attribute $a$, $a \in$ {intensity/color, texture, phase}. $w(a)$ is the weighting coefficient associated with image attribute $a$.

The flow direction needs to be estimated as well. At each location $s$ in the image, we have {[$E(s, \theta)$, $P(s, \theta)$, $P(s,$

$\theta+\pi$)]|0≤$\theta$≤$\pi$}. We first identify a continuous range of flow directions which maximizes the sum of probabilities in a corresponding half plane:

$$\Theta(s) = \arg\max_{\theta} \left\{ \sum_{\theta(s)\le\theta'<\theta+\pi} P(s,\theta') \right\} \tag{12}$$

The edge flow vector is then defined to be the following vector sum:

$$\vec{F}_{(s)} = \sum_{\Theta_{(s)}\le\theta<\Theta_{(s)}+\pi} E_{(s,\theta)}.\exp(j\theta) \tag{13}$$

where $\vec{F}_{(s)}$ is a complex number with its magnitude representing the resulting edge energy and angle representing the flow direction.

### C. Active Contour Model with Gradient Vector Flow

In 1997, Zu and Prince [9] developed technique using gradient vector flow as external force of active contour model

They defined new static external force field $F_{ext}^{g} = v(x,y)$ that was called gradient vector flow field and substituted $-\nabla E_{ext}$ to solve dynamic equation (6). Replacing $-\nabla E_{ext}$ with $v$, we obtain:

$$x_{(t)}(s,t) = \alpha x''(s,t) - \beta x''''(s,t) + v \tag{14}$$

Equation (12) shows the edge map $f(x,y)$ that was initially derived from image $I(x,y)$

$$f(x,y) = -E_{ext}^{i}(x,y) \tag{15}$$

The gradient vector flow field was defined as $v(x,y) = [u(x,y), v(x,y)]$ that minimizes the energy functional:

$$\varepsilon = \iint \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |v - \nabla f|^2 dxdy \tag{16}$$

Using Calculus of variations, then gradient vector flow field was solved by Euler equation

$$\mu\nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0 \tag{17}$$

$$\mu\nabla^2 v - (v - f_y)(f_x^2 + f_y^2) = 0 \tag{18}$$

From equation (17) and (18), the solution can be obtained by defined $u$ and $v$ as a function of time.

$$\begin{aligned} u_t(x,y,t) &= \mu\nabla^2 u(x,y,t) - [u(x,y,t) - f_x(x,y)] \\ &\quad \cdot [f_x(x,y)^2 + f_y(x,y)^2] \end{aligned} \tag{19}$$

$$\begin{aligned} v_t(x,y,t) &= \mu\nabla^2 v(x,y,t) - [v(x,y,t) - f_y(x,y)] \\ &\quad \cdot [f_x(x,y)^2 + f_y(x,y)^2] \end{aligned} \tag{20}$$

Using numerical technique, $u$ and $v$ are defined as an iteration solution:

$$\begin{aligned} u_{i,j}^{n+1} &= (1 - b_{i,j}\Delta t)u_{i,j}^{n} + r(u_{i+1,j}^{n} + u_{i,j+1}^{n} + u_{i-1,j}^{n} \\ &\quad + u_{i,j-1}^{n} - 4u_{i,j}^{n}) + c_{i,j}^{1}\Delta t \end{aligned} \tag{21}$$

$$\begin{aligned} v_{i,j}^{n+1} &= (1 - b_{i,j}\Delta t)v_{i,j}^{n} + r(v_{i+1,j}^{n} + v_{i,j+1}^{n} + v_{i-1,j}^{n} \\ &\quad + v_{i,j-1}^{n} - 4v_{i,j}^{n}) + c_{i,j}^{2}\Delta t \end{aligned} \tag{22}$$

where

$$r = \frac{\mu\Delta t}{\Delta x \Delta y} \tag{23}$$

### D. Edge Flow Vector for Active Contour Model

We propose a new algorithm for texture segmentation. In our approach, there are two new definitions, the new external energy aid the new external force field. We define the external energy for active contour as follows. After the edge flow vector ($\vec{F}_{(s)}$) of an image is computed, we perform the edge flow propagation. At each location, the edge flow energy is transmitted to its neighbor in the direction of flow if the neighbor also has a similar flow direction (the angle between them is less than 90°). The propagation is terminated where two opposite direction of flows encounter each other. Once the edge flow propagation reaches a stable state, the external energy can be computed by using non-zero edge flows coming from two opposite directions. Let us define by $V(x,y)$ and $H(x,y)$ as the vertical and horizontal edge flow maps. Let $\vec{F}_f(s)$ be the final stable edge flow vector. $\vec{F}_f(s)$ can be further represented as $(a(x,y),b(x,y))$= (real($\vec{F}_f(s)$),imag($\vec{F}_f(s)$)) . $V$ and $H$ are defined as:

$$V(x,y) = \begin{cases} a(x-1,y) - a(x,y) & \text{if } a(x-1,y) > 0 \text{ and } a(x,y) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

$$H(x,y) = \begin{cases} b(x,y-1) - b(x,y) & \text{if } b(x,y-1) > 0 \text{ and } b(x,y) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

The new external energy can now be defined as:

$$f(x,y) = -(V(x,y) + H(x,y)). \tag{26}$$

We define the edge flow vector to be the vector field $v(x,y)=[a(x,y),b(x,y)]$ that minimizes the energy functional

$$\varepsilon_{ef} = \iint u(a_x^2 + a_y^2 + b_x^2 + b_y^2 + |\nabla f|^2 |v - \nabla f|^2 dxdy. \tag{27}$$

Using the standard numerical implementation method as described in equation (19) to (23) by replacing $u_t(x, y, t)$ as $a_t(x, y, t)$ and $v_t(x, y, t)$ as $b_t(x, y, t)$, the energy minimization can be solved.

## III. EXPERIMENTAL RESULTS

We demonstrated the useful of our new approach for texture segmentation. We compared our result with several traditional methods. Fig. 2 show several results of energy functional. Fig. 2 (b) and Fig. 2 (c), shown energy map from standard gradient, GVF and edge flow energy, respectively. It was clear that, for texture image, the edge flow energy is large on the boundary between two texture regions. This can be used to terminated the active contour where the energy is minimized (-($V(x, y)$+$H(x, y)$)). The initialization was shown in Fig. 3. Fig. 4 shows the results in intermediate iteration. It was shown that only our proposed method can determine the correct boundary between two texture objects. Fig. 5 to Fig. 7 show another example results. Again, our proposed method (ACM+EF Vector) outperformed the traditional one.

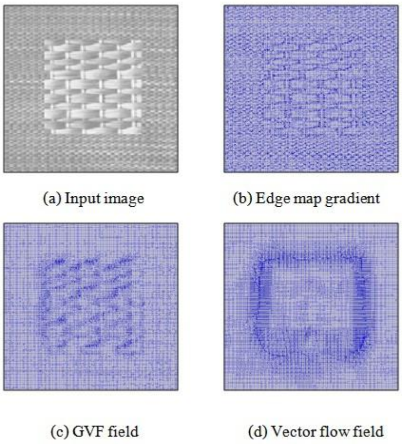


Fig. 2. Sample image with two texture.

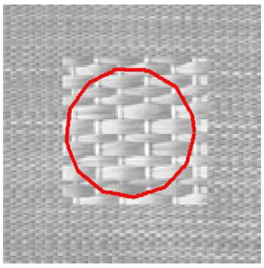

Fig. 3. Initialization with two texture image.

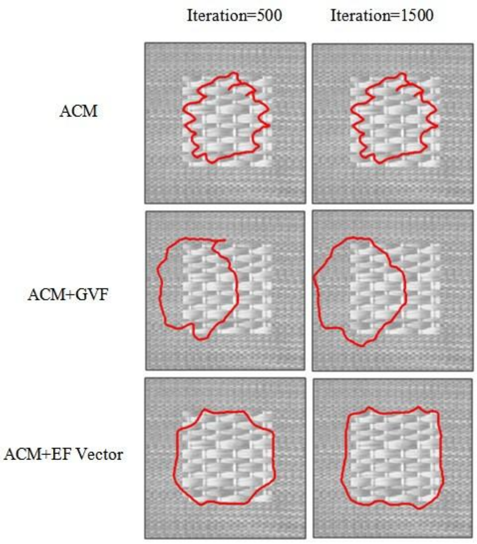


Fig. 4. Comparison of traditional active contour model, active contour model with gradient vector flow and active contour model with edge flow vector in two texture image.

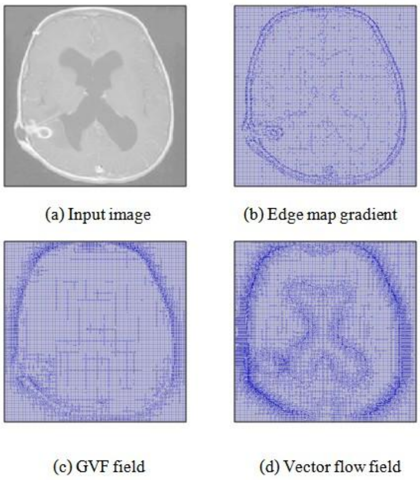


Fig. 5. Sample image with MRI.

Fig. 6. Initialization with MRI image.

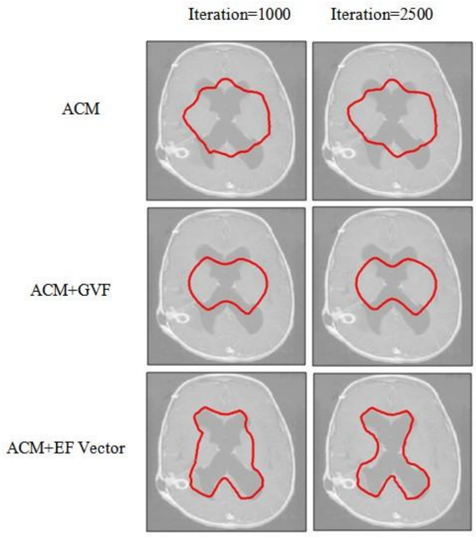


Fig. 7. Comparison of traditional active contour model, active contour model with gradient vector flow and active contour model with edge flow vector in MRI image.

## IV. DISCUSSION

It was observed that image after segmented using traditional active contour model and active contour model with gradient vector flow was unable to identify texture object. As consider the principle of traditional active contour model and active contour model with gradient vector flow, the traditional active contour model don't have contour guider and active contour model with gradient vector flow used gradient vector flow as contour guider. They identified tracery in texture as edge, thus the texture object after segmented using those techniques were unclear to be identified or separated from the initial image. In contrast with our technique, we use edge flow vector as contour guider in active contour model. The edge flow vector identifies flow direction of each pixel near boundary. The direction of edge flow vector compare with gradient vector is more directional to the texture boundary. Thus, using edge flow vector in active contour model in texture segmentation made texture could be identified and tracery was known that it was not the edge of object. As results, the active contour model with edge flow vector gave better image quality after segmented and more suitable for texture segmentation.

## V. Conclusion

The results of texture segmentation using active contour models with edge flow vector reveal that texture object can be separated from initial image with better quality. Comparing with traditional method and active contour models with gradient vector flow, they were unable to identify edge of texture object in the initial image. Because direction of edge flow vector is more directional to the texture boundary, thus using the edge flow vector as a contour guider in active contour models can improve capability of active contour model for texture segmentation.

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**Tanunchai Boonnuk** is studying the doctor of engineering at the Electrical Engineering Graduate Program, Faculty of Engineering, Mahanakorn University of Technology, Bangkok, Thailand. His current research interest is texture segmentation by using active contour model.

**Sanun Srisuk** is the dean and an assistant professor at Faculty of Industrial Technology, Nakhon Phanom University, Nakhon Phanom, Thailand. His current research interests are face recognition, face verification system, face authentication, discrete wavelet transform, varying illumination, Gabor quotient image, trace transform.

**Thanwa Sripramong** is an assistant professor at Faculty of Engineering, Mahanakorn University of Technology, Bangkok, Thailand. His current research interest are evolutionary algorithms, automated circuit synthesis using genetic programming, human-machine interfacing, fault-tolerant system, crital system design, embedded system and application.