

Pathway Extraction using Snakes with GPS Initialization

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Introduction

The extraction of features from digital images is one of the core problems facing computer vision. For GIS applications one of the most critical features to be extracted is pathways: roads and trails. To date, most methods are not general purpose; they are either application or image specific. One of the more general and popular methods is that of active contours or snakes due to Kass et al [2]. A snake is a deformable model that uses energy minimization techniques to find contours in images and extract features. They have gained wide acceptance and have been applied to and modified for many problems.

A key weakness of the snakes model is that the contours (snakes) require initialization. Typically initialization is done by the user (by hand), or by either ad hoc or application specific methods. We propose using GPS data as initialization. Since even recreational GPS units are typically accurate to within 5-6 meters [6] they provide an excellent rough estimate of a pathway.

The traditional snake model is designed to extract features given varied initializations. This paper presents a new energy functional that exploits properties of GPS data to strengthen the ability of the snake to extract a pathway.

Snake Energy Formulation

The energy functional of a snake is expressed in terms of internal and external energy [2]. The internal energy is dependent only on the shape and characteristics of the contour while the external energy is derived from image information. Let the snake be defined parametrically as $v(s) = (x(s), y(s))$. Then, the total energy of the snake is defined as

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

Internal Energy

Traditionally, the internal energy is defined using first and second order continuity constraints [2]. These constraints control the elasticity and stiffness (respectively) of the contour as it shrinks around an image object. The internal energy is used to control and modify the overall shape of the contour.

This definition of internal energy is not well suited for a snake formulation using GPS initialization. In fact, it has been our experience that the initial shape of the GPS data should be preserved, not altered. Large differences from the initial shape should only be

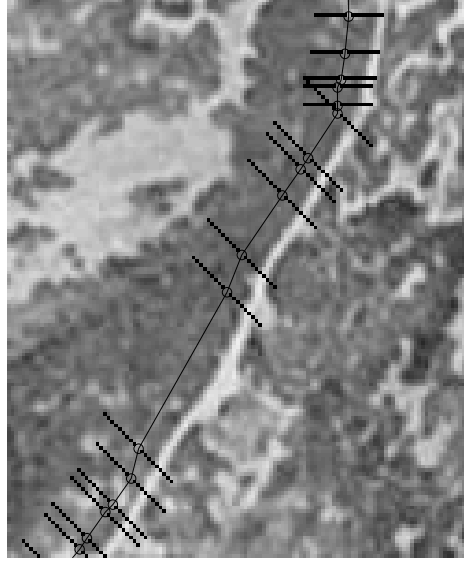


Figure 1: DOQ [4] image with GPS data plotted showing θ direction

allowed under strong image evidence. Therefore, we define a new internal energy term to penalize deviations from the initial shape. Let $g(s)$ be the fixed parametric curve defined by the initial GPS data. Using a constant tuning parameter β , the internal energy is defined as

$$E_{gps-int} = \beta |g(s) - v(s)|^2 \quad (2)$$

External Energy

The external energy is typically defined using the image intensity function and derivatives of it. This attracts the snake to areas of high intensity as well as to edges in the image. We include an image intensity term but have found edges in images to be unreliable, especially when attempting to extract trails of narrow width.

As seen in figure 1, a pathway will be locally maximal in the direction perpendicular to the direction it is traveling. Due to GPS initialization we know the overall structure of the pathway beforehand. We can then precompute, for each region along the snake, which orientation to use for a check of local maximality. We incorporate this into our external energy term. Let $\theta(s)$ be defined as the angle between a reference line and the line perpendicular to g at s . Then the external energy is defined as:

$$E_{gps-ext} = \omega I(x, y) + \zeta \frac{\partial I}{\partial \theta(s)} \quad (3)$$

The first term in the summation is simply the image intensity with ω , a tuning parameter. The second term is modified by the tuning parameter ζ . Its derivative is one dimensional taken in the direction of $\theta(s)$, which is a fixed function computed solely from g , the initial curve. Example θ directions are shown in figure 1.

The solution of the active snake model is the curve, v , such that E_{snake} is minimal. Therefore, minimizing $E_{gps-ext}$ will move the snake towards local maximums in the direction of θ . Minimizing the first derivative moves towards local maxima or minima and the $\omega I(x, y)$ term with ω negative ensures maxima over minima.

Implementation: Greedy approach

We have solved our snake formulation using the greedy approach described in [5]. We chose this approach for ease of implementation, speed and due to the inherent locality of corrections in our problem. Other solution techniques for energy functionals of this form include gradient descent derived from variational calculus [3] and dynamic programming [1]. The former suffers from numerical instability while the latter provides a globally optimal solution at a high computational cost.

An iteration of the greedy algorithm proceeds by walking the list of GPS points. Let P_i be the i -th point of the GPS track. The algorithm considers each pixel in a Δ by Δ window around P_i as a possible position to move P_i to. For each location in the Δ window the algorithm computes the change in energy for P_i that will result if P_i is moved to that pixel. The pixel with the minimum energy is chosen for the new location of P_i .

The correction obtained for point P_i is used to predict and penalize corrections for point P_{i+1} . The distance from this predicted correction is used as a local approximation to the internal energy term. This has the effect of maintaining the overall shape of the GPS track while allowing runs of local corrections. The external energy term is approximated by a measure of local maximality in the θ direction.

Results

In practice, the greedy implementation of our energy formulation performs well at correcting GPS tracks. Figure 2 shows a DOQ image with an initial GPS track and its snake corrected result plotted on it. We have tested the code on a variety of images of varying terrain. We have found the results to be more than satisfactory. Quite often, parameter tuning was not necessary; the same values of the constants given in Figure 2 worked well.

Acknowledgment

Scott Morris is supported by a Department of Education GAANN fellowship.

References

- [1] Amir A. Amini. Using dynamic programming for solving variational problems in vision. *PAMI*, 12(9):855–867, Sept. 1990.
- [2] A. Witkin M. Kass and D. Terzopoulos. Snakes: Active contour models. *Proceedings of the IEEE International Conference on Computer Vision*, pages 259–268, 1987.

