SEMI-AUTOMATED FEATURE EXTRACTION USING SIMULATED ANNEALING

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ABSTRACT

An efficient semi-automatic feature extraction technique that integrates the principles of the active contour models (Kass et al 1988) with simulated annealing (Kirkpatrik et al 1983) is proposed in this article. The methodology in its initial phase requires the application of appropriate image processing techniques, computation of the energy image and a rough delineation of the feature of interest by the user. Subsequently, B-splines are used to model the initial user delineated points and a window containing both the spline and the feature of interest is considered. The searching capability of simulated annealing is then exploited for evolving a minimum energy state in a rectangular window around the delineation for extracting the feature appropriately. Comparison of the performance of the proposed algorithm with *snakes*, another common feature extraction technique based on energy minimisation, demonstrates the superiority of the former for situations where the initial delineation does not closely approximate the feature of interest.

1 INTRODUCTION

In computer vision and digital photogrammetry, feature extraction (Merlet and Zerubia 1996, Brown and Marin 1995, Helmut et al 1997, Gruen and Li 1994) from remotely sensed imagery has been an area of active research for the last few decades. Although the design of automatic techniques (Trinder and Wang 1998, Helmut et al 1997) for extraction of features may be the ultimate goal, some intervention by the operator is still regarded to be important and useful, thus leading to the development of semi-automatic feature extraction schemes (Wong et al 1998, Trinder and Li 1995). This is because experienced human observers still have superior imaging understanding capabilities to currently available feature extractors based on computer vision procedures. Hence, semi-automatic methods are usually more efficient for the extraction of cultural information from aerial and satellite images. An important aspect, therefore, is to use human intervention intelligently, while keeping the level of interaction to minimum. Semi-automatic feature extraction methods also decrease the overall complexity of the feature extraction process, and hence are more easily understood by operators involved in information extraction for digital mapping and GIS.

Kass et al. (1988) have proposed active contour models (*snakes*) for feature extraction that map the problem into one of energy minimization. The basic principle is to derive, from an initial estimate of the feature, a smooth contour with minimum energy. The main disadvantage of *snakes* is that the solution is dependent upon the initial state, i.e. positions defined by the the user, and may be incorrectly influenced by local energy minima near the initial locations in the search space. Moreover it also suffers from the computational complexity of deterministic dynamical systems with many degrees of freedom. Since the concept of energy minimisation embedded in the active contour model is analogous to the principles of simulated annealing (SA) (Kirkpatrik et al 1983, Press et al 1986), the application of SA for feature extraction seems appropriate.

Simulated annealing mimics the principles of the annealing procedure, which is a physical process where a crystal is cooled down from liquid to a solid phase. Simulation of this physical cooling may be done with the Metropolis algorithm. It generates sequences of states in the following way:

> Given a current state C_i with energy E_i, the next state C_j (with energy E_j) is generated by applying a small perturbation in C_i. If $E_j - E_i$ is less than or equal to 0, then C_j is accepted as the current state. Otherwise, it is accepted with a probability $\exp(-\frac{E_j - E_i}{k_\beta T})$, where T and k_β represent the temperature and Boltzmann's constant respectively. If the lowering of the temperature is done slowly enough, the crystal reaches thermal equilibrium at each temperature. In the Metropolis algorithm, this is achieved by applying a sufficiently large number of perturbations at each temperature.

In this article we integrate the principles of the active contour models (Kass et al 1988) with simulated annealing (Kirkpatrik et al 1983) to design an efficient semi-automatic feature extraction technique. It is important to note that a given image may have several structures resembling the feature of interest (e.g., linear feature). It is therefore essential to approximately specify the structure in which the user is interested. Moreover, in order to restrict the search space of SA, we have incorporated a windowing approach in the algorithm.

In this implementation, appropriate image processing techniques are applied initially and the energy image is computed. Subsequently the operator determines the location of an active contour by interactively placing some points of the feature near the image structure of interest which is taken as the initial state. B-splines are used to fit the initial user delineated points and a rectangular window containing both the spline and the feature of interest is considered. Finally, SA is used to provide an accurate estimate of the feature of interest by minimizing the energy of the state in the window. The superiority of the method over the *snakes* model is demonstrated on a 2-D aerial image.

2 SIMULATED ANNEALING FOR FEATURE EXTRACTION

2.1 Preprocessing

Procedures to extract features from digital remotely sensed data typically involve initially the application of low level image processing techniques. These require determination of sufficient attributes such as, edge gradients, texture, shadow, etc., in the image to adequately define the features. Usually, some contrast and image enhancement techniques are used to emphasize the characteristics of the image in the first stage. Moreover, noise reduction techniques are also applied to reduce the effects of misleading information in the images. The extraction of linear features by semi-automatic methods in this paper subsequently involves the application of edge detector algorithms (Canny 1986, Fua and Lecler 1990).

2.2 Formulation of Total Energy

Total energy in an image can be defined as sum of *internal* and *external* energies (Kass et al 1988). This may be expressed by a parametric representation of the contour, $\nu(s) = (x(s), y(s))$, as

$$E = \int_{s_0}^{s_1} E(\nu(s))ds = \int_{s_0}^{s_1} [E_g(\nu(s)) + E_p(\nu(s)) + E_c(\nu(s), \nu_0(s))]ds. \tag{1}$$

Here the intrinsic or geometric energy E_g is derived from the geometric constraints of the object model. Normally E_g is based on the first derivative (ν_s) and the second derivative (ν_{ss}) of the function defined by $E_g = \alpha|\nu_s(s)|^2 + \beta|\nu_{ss}(s)|^2$, where α and β are constants that control the influence of the geometric energy against the photometric energy. B-splines are used to model the feature in this implementation. The advantages of the spline are that they are smooth piecewise polynomial which maintain continuity between neighbouring domains. The extrinsic energy comprises photometric energy E_p, that constrains the contour to approach the feature of interest, and control energy E_c, which constrains the difference between the contour $\nu(s)$ and the initial curve $\nu_0(s)$. E_p, derived from the image, depends on the type of feature to be extracted. For a narrow linear feature, it can be the square of intensity values ($I(x, y)$) of the image, multiplied with a positive or negative constant (w) for lighter or darker features respectively. i.e., $E_{pl} = w|I(x, y)|^2$. For a step edge, it can be calculated as, $E_{pe} = -|\delta I(x, y)|^2$, thus helping the contour to move towards the image points with high gradient values while minimising the energy.

In this article, the features in the image are defined by morphological tools for narrow features and the Canny operator (Canny 1986) for step functions as were used in (Trinder and Li 1995). The *energy image* is defined by a Chamfer image, derived from the feature image, in which the pixel values relate to their closeness to any surrounding edge. Letting $E_{ext} = E_p + E_c$, equation (**??**) becomes

$$E = \int_{s_0}^{s_1} [\alpha|\nu_s(s)|^2 + \beta|\nu_{ss}(s)|^2 + E_{ext}(\nu_s(s)) = \int_{s_0}^{s_1} F(s, \nu, \nu_s, \nu_{ss})ds \tag{2}$$

The computation requires the minimisation of this energy.

2.3 Energy Minimization Using Simulated Annealing

2.3.1 Basic Principle The feature of interest is first roughly delineated by the operator by control points. The B-spline will be computed to model this feature. A rectangular window $\mathcal{W}$ is defined in the image from the initial user delineation in such a way that it includes the feature of interest. The aim of the process is to gradually update the location of the B-spline, subsequently referred to as modified B-spline, by minimising the energy such that on termination of the process, it will represent the correct location of the feature of interest. Note that in the SA process, the B-spline and its subsequent modifications, are obtained by perturbing any one pixel at a time. Thus the total number of pixels in the B-spline or modified B-spline remain constant.

Considering the configuration of $\mathcal{W}$ that contains the B-spline (or modified B-spline) and the feature of interest as the state $\mathcal{S}$, the SA based feature extraction technique attempts to provide its estimate of the feature of interest by minimizing the energy of the configuration. The energy, $\mathcal{E}_S$, corresponding to the state $\mathcal{S}$ at any instant is computed as

$$\mathcal{E}_S = \sum_{i=1}^{p} e_i \tag{3}$$

where, e_i and p represent the energy at pixel x_i and total number of pixels in the B-spline respectively.

2.3.2 Simulated Annealing In SA, the temperature T is first raised to T_{max} and then gradually cooled, according to some temperature schedule, to T_{min}. Let the initial state and its associated energy be represented by $\mathcal{S}$ and $\mathcal{E}_S$ respectively. As mentioned earlier, the task of SA is to generate a new state $\mathcal{S}'$, reject or accept it based on the energy values of $\mathcal{S}$ and $\mathcal{S}'$, and attempt to minimize $\mathcal{E}_S$ in the process. The basic steps of SA, are shown in Figure. **??**.

1. $T = T_{max}$
2. Initialise state ($\mathcal{S}$) with energy $\mathcal{E}_S$.
3. while($T > T_{min}$)
4. begin
5. for i=1 to N_T do /* N_T is the number of iterations at temperature T*/
6. begin
7. Evolve state $\mathcal{S}'$ with energy $\mathcal{E}_{S'}$ by randomly removing one pixel from $\mathcal{S}$ and subsequently adding one to it (i.e., to $\mathcal{S}$) which is not in $\mathcal{S}$.
8. If($\mathcal{E}_{S'} - \mathcal{E}_S \leq 0$) $\mathcal{S} \leftarrow \mathcal{S}'$
9. Else $\mathcal{S} \leftarrow \mathcal{S}'$ with probability $\exp(-\frac{\mathcal{E}_{S'} - \mathcal{E}_S}{T})$
10. endfor
11. $T \leftarrow T \times \alpha$
12. endwhile

Figure 1: Basic steps in SA

Generation of $\mathcal{S}'$ from $\mathcal{S}$: From the B-spline or the modified B-spline (corresponding to $\mathcal{S}$), a pixel x_i is chosen randomly for mutation. This pixel (x_i) is replaced by another pixel x_j in $\mathcal{W}$ which is not already in $\mathcal{S}$ to generate $\mathcal{S}'$. The energy of $\mathcal{S}'$ is computed by

$$E_{S'} = E_S - e_i + e_j.$$

Temperature scheduling : In this article we have used a geometric temperature schedule of the form $T_{t+1} = \alpha * T_t$, where α is a positive real number close to zero. The value of α in the range [0.6,0.9] and $T_{max} = 50$ were found to be well suited for our purpose. It was found that the rate of convergence of the process increased with the increase in α values within the specified range. As $T_t \rightarrow 0$, no more perturbations of the state were possible and hence the termination condition was assumed to be reached. In practice, the system state is found to be 'frozen' well before this step was reached.

3 IMPLEMENTATION AND RESULTS

The different steps used in the simulated annealing based feature extraction procedure are as follows.

1. Preprocessing by image stretching
2. Edge detection by
   - Canny operator for single edges, such as dividing lines between features or edges of roads on aerial photography.

- Morphological tools for narrow features, such as roads on satellite images.
- To detect bright small elements, erosion followed by a dilation is applied; then the original image is subtracted from this result.
- For dark small elements, dilation is applied first, then erosion.

3. Derivation of a chamfer image in which the pixel values relate to their closeness to any surrounding edge.
4. Acquisition of control points (initial curve) from the user that roughly delineates the feature
5. Smoothing the initial curve using B-spline and initialize its state
6. Minimize the energy of the state using SA

Figures. **??**, **??**, and **??**, **??**, demonstrate the performance of the *snake* and SA based method respectively for different initial configurations. The white curves in the figures represent the B-spline drawn from the user provided control points while the black lines represent the final solution. As can be seen from Figure. **??** the *snake* is able to provide a good estimate of the feature of interest only when the initial approximation is quite close to it, but it becomes distorted by suboptimal solutions otherwise (see Figure. **??**). On the other hand, the SA is found to provide a good estimate of the feature of interest even when the initial delineation is well away from it (see Figures. **??** and **??**).

4 DISCUSSION

An efficient semi-automatic feature extraction technique which integrates the principles of active contour models with simulated annealing is developed in this article. The power of the annealing procedure for providing stable minimum energy configuration has been utilized along with the principle of active contours to search for appropriate feature delineation which minimises the energy. The significant superiority of the developed technique over the *snakes* model is demonstrated on an aerial image for several initial configurations. Note that *snakes* may become distorted by local energy minima, depending on the initial user delineation and repeated reinitialisations are required each time this happens. Moreover, *snakes* are found to provide a good solution only when the initial user delineation is quite close to the feature of interest. The developed technique does not suffer from either of these limitations, the only requirement being that the window size is large enough so as to include the feature of interest. Note that the pull-in range of the SA based method is governed by the size of the window. Therefore, increasing the size of the window will increase the pull-in range of the method, at the cost of increase in its run time.

In this context, it may be mentioned that if more than one feature of interest is present in the window, then the SA based method would capture points from all such features, thereby resulting in the loss of structural continuity in the final solution. Additional terms may be incorporated in the energy function, which will automatically enforce the structural continuity of the contour provided by the algorithm. Preliminary investigation in this regard are already being carried out by the authors.

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Figure 2: Feature Extraction Using Snake after 50 Iterations for Initial Configuration 1

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Figure 3: Feature Extraction Using Snake after 50 Iterations for Initial Configuration 2

Figure 4: Feature Extraction Using Simulated Annealing with Rectangular Window for Initial Configuration 3

Figure 5: Feature Extraction Using Simulated Annealing with Rectangular Window for Initial Configuration 4