Snake Head Boundary Extraction using Global and Local Energy Minimisation

Steve R. Gunn and Mark S. Nixon

Image, Speech and Intelligent Systems Group Department of Electronics and Computer Science University of Southampton

21 September 1996

Abstract

Snakes are now a very popular technique for shape extraction by minimising a suitably formulated energy functional. A dual snake configuration using dynamic programming has been developed to locate a global energy minimum. This complements recent approaches to global energy minimisation via simulated annealing and genetic algorithms. These differ from a conventional evolutionary snake approach, where an energy function is minimised according to a local optimisation strategy and may not converge to extract the target shape, in contrast with the guaranteed convergence of a global approach. The new technique employing dynamic programming is deployed to extract the inner face boundary, along with a conventional normal-driven technique to extract the outer face boundary. Application to a database of 75 subjects showed that the outer contour was extracted successfully for 96% of the subjects and the inner contour was successful for 82%. The results demonstrated the benefits that could accrue from inclusion of face features, giving an appropriate avenue for future research.

Keywords: Snakes, Active Contours, Head Boundary

1 Introduction

The objective of this research is to develop robust active contour techniques which are suitable for the extraction of the head boundary. A dual active contour has been developed previously (Gunn and Nixon, 1995) which relieved difficulty in contour initialisation and reduced the number of parameters controlling evolution. The technique uses two contours to seek a global energy minimum between two initial contours. The concept of a dual contour for initialisation can be used with dynamic programming to guarantee the global energy minimum in a non-evolutionary manner. Dynamic programming is an optimal exhaustive minimisation technique, unlike other global minimisation strategies such as simulated annealing, (Rueckert and Burger, 1995; Storvik, 1994). Amongst previous active contour methods implemented with dynamic programming, one implemented the original gradient descent minimisation to find local energy minimu (Amini et al., 1990), whereas others have aimed for a global solution (Geiger et al., 1995; Lai and Chin, 1995). Dynamic programming is particularly suited to the minimisation of the snake since dependency is local within the snake model. In this paper we focus on the merits of the conventional snake approaches and the search-based approaches. These are applied to extract the head and face boundary in face images. Location and description of these boundaries is important in facial feature extraction (C.L.Huang and Chen, 1992) and in model-based coding (W.J. Welsh and Waite, 8).

Classical techniques based on local edge data are limited by their inability to provide an implicit description, which active contours provide. Waite and Welsh (1990), Lam and H.Yan (1994) and C.L.Huang and Chen (1992) have all used snakes, using a closed contour, to extract the head boundary. However, the extracted

boundaries differ; Waite extracts a boundary including the chin and the upper part of the hair using an external contracting contour, whereas Huang and Lam extract the boundary of the chin and lower part of the hair using an internal expanding contour. Lam takes account of the actual face, by heuristically varying the snake parameters around the face boundary. Lam and Huang both use the greedy method (Williams and Shah, 1992) for the active contour technique. This technique is fast, but is restricted by the inability to guarantee a local minimum solution. As with the previous approaches, our new approach uses front view face images. Our



FIGURE 1: Head Boundary Definitions

approach uses two contours; an open contour to extract the outer head and shoulders' boundary and a closed contour to extract an inner boundary of the chin and inner hair line, Figure 1. In order to extract the inner and outer head boundaries two different active contour approaches are employed. An evolutionary (conventional) approach which has an outlining capability and is compatible with the extraction of the outer contour and a search-based technique which is better suited to the extraction of the inner contour, where an unobstructed initialisation is unrealistic. By application to a face database of 75 images, we show how this new technique can extract the boundaries of interest successfully.

2 Snakes

The original snake model was introduced by Kass et al. (1988). A contour is described parametrically by $\mathbf{v}(s) = (x(s), y(s))$ where x(s), y(s) are x, y co-ordinates along the contour and $s \in [0, 1)$ is normalised arc length. The snake model defines the energy of a contour $\mathbf{v}(s)$, the snake energy E_{snake} , to be

$$E_{snake}\left(\mathbf{v}(s)\right) = \int_{s=0}^{1} \lambda E_{int}\left(\mathbf{v}(s)\right) + (1-\lambda)E_{image}\left(\mathbf{v}(s)\right) \, ds,\tag{1}$$

where E_{int} is the internal energy of the contour, imposing continuity and curvature constraints, E_{image} is the image energy constructed to attract the snake to desired feature points in the image, $\lambda \in [0, 1]$ is the regularisation parameter governing the compromise between adherence to the internal forces and the external image data; the functional, $E_{image} = -|\nabla I(x, y)|$ attracts the snakes to edges in the image. An initial contour evolves by minimising Equation 1 using a gradient descent technique.

Active contour techniques can be divided into two groups: evolutionary (local) approaches and search-based (global) approaches. Evolutionary approaches follow the original gradient descent technique, whereas search-based techniques search for a global minimum.

2.1 Evolutionary Approach (Local)

The term 'evolutionary' is applied to snakes which use a gradient descent technique. A characteristic of the original snake model (Kass et al., 1988) was that if the snake was not submitted to any image forces it would contract to a point. To enhance versatility, Cohen and Cohen (1993) proposed an additional normal force which

could be applied to the contour. Recent work by Xu et al. (1994) and Gunn and Nixon (1995) has developed alternative schemes for unifying expanding and contracting contours, by removing the internal contraction force without affecting the regularising property.

2.2 Search Approach (Global)

A weakness of the evolutionary, or local minimum, approach is the sensitivity to initialisation and difficulty in determining suitable parameters. This can be exaggerated by noise. To overcome this problem we propose a technique which searches for a global minimum within a specified region, constraining the initialisation as in the dual active contour. This region is described by two initial contours which define a search space for the technique. Dynamic programming is used to search the space for the optimum solution, illustrated in Figure 2. A discrete contour is defined by, $\mathbf{v}_i = (x_i, y_i)$ for $i = 0 \dots N - 1$ where subscripted arithmetic is modulo N



FIGURE 2: Dynamic Programming Contour Space

for closed contours. Each contour point is constrained to lie on a line joining the two initial contours, Figure 2. Each line is discretised into M points for the dynamic programming search. An open contour is especially compatible with minimisation via dynamic programming.

The energy of an open snake is given by,

$$E_{snake}\left(\mathbf{v}(s)\right) = \sum_{i=0}^{N-3} E_i\left(\mathbf{v}_i, \mathbf{v}_{i+1}, \mathbf{v}_{i+2}\right),\tag{2}$$

emphasising the local dependencies, since a point is dependent only on its immediate neighbours for its energy. The energy of a closed snake contains two extra energy terms arising from the joining of the open snake. The upper limit of Equation 2 is adjusted to N - 1 accordingly. The energy at each snake point \mathbf{v}_i is given by

$$E_{i-1}\left(\mathbf{v}_{i-1}, \mathbf{v}_{i}, \mathbf{v}_{i+1}\right) = \lambda_{i} E_{int}\left(\mathbf{v}_{i-1}, \mathbf{v}_{i}, \mathbf{v}_{i+1}\right) + (1 - \lambda_{i}) E_{ext}\left(\mathbf{v}_{i}\right)$$
(3)

where $\lambda_i \in [0, 1]$ is the regularisation parameter.

In order to apply dynamic programming to Equation 3, a two element vector of state variables, $(\mathbf{v}_{i+1}, \mathbf{v}_i)$, is calculated at each stage. The optimal value function, S_i , is a function of two adjacent points on the contour and is calculated as

$$S_{i}\left(\mathbf{v}_{i+1}, \mathbf{v}_{i}\right) = \min_{\mathbf{v}_{i-1}} \left[S_{i-1}\left(\mathbf{v}_{i}, \mathbf{v}_{i-1}\right) + \lambda_{i} E_{int}\left(\mathbf{v}_{i-1}, \mathbf{v}_{i}, \mathbf{v}_{i+1}\right) + (1 - \lambda_{i}) E_{ext}\left(\mathbf{v}_{i}\right)\right],\tag{4}$$

given the initial conditions $S_0(\mathbf{v}_1, \mathbf{v}_0) = 0$.

In addition to the energy matrix corresponding to the optimal value function, a position matrix is also required. Each entry of the position matrix at stage *i* stores the value of \mathbf{v}_{i-1} that minimises Equation 4. The optimality function, Equation 4, is evaluated for $i = 1 \dots N - 2$. The result is obtained by back-tracking through the position matrix. The internal energy function is given by

$$E_{ext}\left(\mathbf{v}_{i-1}, \mathbf{v}_{i}, \mathbf{v}_{i+1}\right) = \left(\frac{\mathbf{v}_{i+1} - 2\,\mathbf{v}_{i} + \mathbf{v}_{i-1}}{\mathbf{v}_{i+1} - \mathbf{v}_{i-1}}\right)^{2}.$$
(5)

The numerator is the discrete curvature term from the original snake. The continuity term is less important because point spacing is controlled by constraining the points to lie on the specified lines. The denominator ensures that the internal energy is scale invariant giving no preference for large or small contours, only smooth ones.

The efficiency of dynamic programming is compromised when applied to closed contour problems. To guarantee a global minimum, using the method of (Geiger et al., 1995), requires a separate optimisation to be calculated for all values of \mathbf{v}_0 and \mathbf{v}_1 , incurring an M^2 increase in complexity over the open contour optimisation. To avoid this increase we propose an approximate solution using a two stage technique which transforms the problem into two open contour optimisations. First an open contour solution is found, which does not apply any continuity or smoothness constraints at the ends. The two points at the mid point of this contour are then taken as the start and end points for the closed contour. A second optimisation of the energy function given in Equation 3 is computed with the fixed \mathbf{v}_0 and \mathbf{v}_1 . The optimality function, Equation 4, is evaluated for i = 1...N. By fixing the two points \mathbf{v}_0 and \mathbf{v}_1 the closed contour optimisation can be achieved. Experimental results support the validity of the approximation used.

The search-based technique is not prejudiced to solutions near the initialisation as with evolutionary-based normal-driven techniques, but considers all solutions within the initialisation region. Furthermore it avoids the difficult problem of determining the evolution parameters, and requires a single regularisation parameter.

3 Head Boundary Extraction

Implementation of these techniques assumes a front-view face image on a plain background. An initial estimate of the head boundary is required to prime the normal-driven snake. Alternative methods for locating the head boundary from a complex background include, a difference image exploiting temporal properties (Turk and Pentland, 1991), and neural networks (Sung and Poggio, 1995) searching to locate facial features. In our study, the emphasis is placed on the extraction technique. Accordingly a simple location scheme based on a binary edge image is employed. A convex hull is used to extract a suitable contour representation from this image to provide an initialisation for the outer contour. The outer contour uses a conventional evolutionary-based technique. The inner contour extraction uses the results of the outer contour to calculate a suitable search space for the initialisation for the inner search-based technique.

3.1 Outer Extraction

The extraction of the outer contour makes the assumption that the head is on a plain background. Consequently any edge data must lie on the boundary or within the head. The original head images are intensity normalised, filtered using a 9×9 Gaussian mask (σ =1.0) and then passed through a first-order gradient-based edge operator. The resulting image is then thresholded to obtain a binary edge image. A fixed threshold value was used, which was selected to extract those parts of the edge image with intensity above the edge noise floor. The initial contour is obtained by generating an open convex hull. The end points are initially determined by searching with a vertically scanning technique, as in Figure 3. The resulting convex hull provides the initialisation for an open contour. This contour is then minimised according to an evolutionary based strategy. A normal force is applied to push the contour towards the head boundary and allow the contour to find non-convex solutions. The normal force parameter was determined heuristically on a limited selection of images, and was then fixed for the remainder of the tests.



FIGURE 3: Convex Hull Extractions

3.2 Inner Extraction

The inner boundary is more difficult to extract with a local minimum based technique due to the quantity of edge data in the face boundary region. To develop a robust extraction technique it is necessary to use a search based strategy which overcomes the sensitivity to initialisation of the evolutionary techniques. Furthermore a particular problem in the extraction of head boundaries is that the chin is often poorly characterised in the edge functional as a consequence of poor image contrast. Normal driven techniques will often drive the snake out of the weak minimum associated with the chin. The search-based technique has a greater tolerance with respect to initialisation than a comparable evolutionary technique.

To provide an initialisation, simple geometrical reasoning about the outer boundary is used, Figure 4. The search space uses the centroid of the outer contour as its origin. The outer part of the search region is comprised of the top half of the outer contour augmented with a semi-ellipse to complete the bottom half. The semi-ellipse has a fixed aspect ratio of 1.5. The inner region is defined by a circular contour, of radius equal to half the minor axis of the ellipse. The circle is vertically offset by a constant factor. A constant value of $\lambda = 0.7$ was used for the regularisation parameter, making no distinction between different parts of the face boundary. The number of snake points was fixed at N=64, and the constraint lines were subdivided into M=40 points.



FIGURE 4: Inner Contour Search Space

4 Results

The head boundary extraction technique was applied to a face database comprising 75 subjects. The database was compiled from an undergraduate portrait session and consequently the majority of subjects are trying to smile and have prepared hair styles. The lighting was controlled, and illuminated the subjects from the front.

	Outline	Inline (inner)	Inline (outer)
Correct	71	61	66
Incorrect	4	14	9

The database included male, female, bearded, spectacle wearers and two subjects wearing head gear. The

TABLE 1: Initialisation results

results of the initialisation were rated according to correctness, Table 1. A correct outline being exterior to the head and terminating at the shoulders. A correct inline describing an annular region containing the inner contour. The inner and outer contour results were overlaid on the original image and the correspondences were assessed. The results were rated as 'excellent', 'good' or 'poor'. 'Excellent' implies that the result could not be improved by manual intervention, whereas a 'good' could, but only for a very small region. A 'poor' result implies that the result is obviously wrong in more than one respect. Alternatively, an empirical measure, as described in (Gunn and Nixon, 1994), could be employed to interpret the results.

The initialisation was successful for 95% of the outer contours and for 73% of the inner contours. Failures in the outer initialisation were mainly due to poor contrast in the hair region. As a result there was no edge marked in the binary edge image causing the convex hull to cut across the head. The failures in the inner initialisation were partly due to the dependence on the outer result, but primarily on the weakness of the geometrical model used to derive the inner contours. Wide faces produced an over-sized interior contour which made the extraction of the correct contour impossible. The outer contour then produced a large region dropping below the neckline. The "good' and 'excellent' categories can be grouped since they only differ by one respect. Considering only the results for which the initialisation was appropriate, Table 2, the outer contour was extracted with a 96% success rate, and the inner contour with a 82% success rate. The results for four of the faces are shown in Figure 5, with (from top to bottom): outer initialisation, outer result, inner initialisation and inner result. Two of the 'excellent' results are subjects, Face 1 and Face 2. The convex hull can be seen to lie on the top of the head and terminate correctly at the shoulders. This primed the open contour well and the outer contour can be seen to track the upper head and shoulders' boundary correctly. This gave a good initialisation for the dynamic programming technique, with an appropriate inner contour. The final inner contour extraction for both faces can be seen to track the inner face boundary correctly. Two faces showing reduced performance are shown, Face

	Outer	Inner
Excellent	37	38
Good	33	12
Poor	5	25

TABLE 2: Head boundary contour results

3 and Face 4. The outer contour in Face 3 and Face 4 are 'good'; for Face 3 the left shoulder is slightly incorrect, and Face 4 misses the left ear slightly, both contours are excellent in all other areas. The inner contours of Face 3 and Face 4 were rated as 'poor'; Face 3 because the edge intensity on the right side of the cheek caused by the subject's smile is more prominent than neighbouring boundary and the final contour included this section erroneously; Face 4 highlights a weakness in the technique whereby the global minimum does not correspond to the full face boundary and could only be compensated for with additional prior information. However, the chin boundary which is often poorly defined is extracted precisely in all the presented results reflecting the performance available from a global approach. Inclusion of face features within the extraction technique appears eminently suitable as an approach to resolve the difficulty with the upper boundary. Accordingly, the technique could be used to provide a set of good solutions which could be passed on to a higher level process, and refined by feedback.

5 Boundary Recognition

This section demonstrates that the extracted contours can be used to discriminate between faces. The internal boundary is used because it contains less information from high variance features, such as the hair. The results

(a) Face 1



(b) Face 2



(c) Face 3



(d) Face 4

FIGURE 5: Head Boundary Extraction Results

that were classed as 'excellent' from the inner contour extraction were assembled to form a known face contour database. Then two 'unknown' inner contours were compared against the 38 'known' contours to find a best match, using a Euclidean metric. The similarity graphs in Figure 6 demonstrate the discriminating ability of the inner face contour. Figure 6(a) and 6(c) illustrate how the 'known' contours of faces 13 and 22 compare with the other 'known' contours, and give an indication of the variance. Figure 6(b) and 6(d) show how the 'unknown' contours of faces 13 and 22 compare to the known database. It can be seen that the technique correctly identifies both faces 13 and 22 as the best match. The measure is no longer zero in both cases giving a similarity of about 5. Figure 7(a)-7(d) illustrates the extracted inner contours used. Figure 7(e) and 7(f) show the two contours which were the most dissimilar to faces 13 and 22.



FIGURE 6: Similarity graphs

6 Conclusions

Implementations of active contour techniques can use evolutionary or global search to determine energy minima in feature extraction. The dual active contour technique has been modified to use dynamic programming to search for a global contour solution within the target region. Extraction by dynamic programming is superior because no evolutionary parameters are used. The two techniques have been shown to provide complementary characteristics for contour extraction. This gives an appropriate basis for head and face boundary extraction.

The new technique has been applied to a database of 75 face images and resulted in a successful extraction rate of 96% for the outer contour and 82% for the inner contour, given a good initialisation. The results showed a need to improve the initialisation techniques for a more robust head boundary technique for, say, a face recognition system. The results demonstrates that with valid initialisations both the evolutionary and search-based active contour technique provide a promising approach for outlining and boundary extraction









(d) Face 22 'unknown' con-(e) Face 18 'known' contour tour

(f) Face 6 'known' contour

FIGURE 7: Inner extracted boundaries

respectively. The main limitation is the dependence upon the quality of the edge detection and the factors affecting this, namely illumination and boundary contrast.

References

- A.A. Amini, T.E. Weymouth, and Jain. Using dynamic programming for solving variational problems in vision. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(9):855-867, 1990.
- C.L.Huang and C.W. Chen. Human facial feature extraction for face interpretation and recognition. Pattern Recognition, 25(12):1435–1444, 1992.
- L.D. Cohen and I. Cohen. Finite-element methods for active contour models and balloons for 2d and 3d images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 15(11):1131–1147, 1993.
- D. Geiger, A. Gupta, L. A. Costa, and J. Vlontzos. Dynamical programming for detecting, tracking and matching deformable contours. IEEE Transactions on Pattern Analysis and Machine Intelligence, 17(3): 294-302, 1995.
- S.R. Gunn and M.S. Nixon. A model based dual active contour. In E. Hancock, editor, Proc. British Machine Vision Conference, pages 305–314, York, U.K., 1994. BMVA Press.

- S.R. Gunn and M.S. Nixon. Improving snake performance via a dual active contour. In V. Hlavac and R. Sara, editors, *Computer Analysis of Images and Patterns*, volume 970 of *Lecture Notes in Computer Science*, pages 600–605. Springer Verlag, 1995.
- M. Kass, A. Witkin, and D. Terzopoulos. Snakes: Active contour models. International Journal of Computer Vision, 1:321–331, 1988.
- K.F. Lai and R.T. Chin. Deformable contours modeling and extraction. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(11):1084–1090, 1995.
- K.M. Lam and H.Yan. Locating head boundary by snakes. In Proc. Int. Symposium on Speech, Image Processing and Neural Networks, Hong Kong, April 1994.
- D. Rueckert and P. Burger. Contour fitting using an adaptive spline model. In Proc. British Machine Vision Conference, pages 207–216, Birmingham, U.K., 1995.
- G. Storvik. A bayesian approach to dynamic contours through stochastic sampling and simulated annealing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 16(10):976–986, 1994.
- K.K. Sung and T. Poggio. Learning human face detection in cluttered scenes. In Proc. Computer Analysis of Images and Patterns, pages 432–439, Prague, 1995.
- M. Turk and A. Pentland. Eigenfaces for recognition. Journal of Cognitive Neuroscience, 3(1):71–86, 1991.
- J.B. Waite and W. J. Welsh. Head boundary location using snakes. *British Telecom Technology Journal*, 8(3): 127–136, 1990.
- D.J. Williams and M. Shah. A fast algorithm for active contours and curvature estimation. CVGIP: Image Understanding, 55(1):14–26, 1992.
- S. Searby W.J. Welsh and J.B. Waite. Model-based image coding. British Telecom Technology Journal, 3 (94–106), 8.
- G. Xu, E. Segawa, and S. Tsuji. Robust active contours with insensitive parameters. *Pattern Recognition*, 27 (7):879–884, 1994.