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APPLICATION OF HOPFIELD NETWORK TO HUMAN-GUIDED CONTOUR EXTRACTION

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ABSTRACT

To develop a contour extraction tool for image simulations, the applicability of the Hopfield network is examined on the edge image around the roughly specified guide points. Our computational theory is that the edge map of the stretched belt-like images along the guide points should obey the following four constraints. (1) In the longitudinal direction, the contour should consist of only one pixel. (2) Contour points are usually located close to those in the neighboring columns. (3) Contour points are usually located on the detected edge pixels in the edge map. (4) Contour points are usually located near the horizontal center of the edge map. Furthermore, to obtain a size independent energy function, we developed a scaling relationship. Using the energy function developed according to these observations, the experimental results are shown in which contour extraction is succesful for the most part.

INTRODUCTION

Recently, simulated images such as color change simulation images and collaged images have been used in many fields.

In most of the cases, when we simulate images, some object regions have to be segmented in advance. This is a very tedious task when the regions are manually cut out pixel by pixel.

At the present stage, unfortunately, fully automatic image segmentation techniques for natural images[1],[2] can be applied only to simple limited cases. Under these conditions, we thought it better to devise an image segmentaion tool which employs guide information, such as the color of the object region or the rough position of the contour.

In this research, the user first gives the rough contour position information and then the Hopfield network[3] is applied to extract the contour from the edge image around these roughly specified guide-points. In our foumulation, we started by constructing the computational theory of the contour extraction in the rectangular images in order to obtain the energy function.

Coefficients of the energy function often depend on the size or the resolution of the system. This is true in our work, too. If our coutour extraction software must locate its parameters, such as energy coefficients, every time the image size changes, then it is a useless tool. In order to construct a size independent energy function, we tried to derive a scaling relationship between the coefficients of the differet sized images by making certain assumptions. Using this scaling relationship, we only have to decide suitable coefficients for one size of the image and then deduce the coefficients of images having different sizes.

In the following sections, the basic formulation of our contour extraction algorithm and the scaling relationships are presented. Then the experimental results are shown.

BASIC FORMULATION

Outline of the Process: In this research, the user specifies the rough contour positions. The outline of the process is as follows.

(P-1) The operator specifies the position coordinates of points along the contour of the region he wants to cut out (typically, 20 or 60 points).

(P-2) Resample the belt-like narrow region along the specified points (**FIG.4**) into a slender rectangular image (typically, 40 or 50 pixel width and 1000 or 2000 pixel length).

(P-3) Get the edge map in the rectangular images using suitable edge detection operations, such as derivatives or zero-crossings (**FIG.5**). In this work, we used zero-crossings.

(P-4) Extract the contour in these rectangular images by operating the Hopfield network (**FIG.6**). In this process, the energy functions which satisfy the computational theory stated in the following subsection are used.

(P-5) Resample the extracted contour in the rectangular images into the original image again and make the detailed contour of the intended region (**FIG.7**).

Computational Theory: In process (P-4), as stated above, we adopted the Hopfield network to extract the contour. Then, we defined the energy function, following the Marr's theory of stereopsis[4] using the computational theory of the contour extraction in the rectangular images.

(C-1) Only one pixel in the longitudinal direction is part of the contour.

(C-2) Neighboring column contour points are usually locate close to another.

(C-3) Contour points are located on the detected edge pixels in the edge map.

(C-4) Contour points are usually located near the horizontal center the edge map.

Energy function: We constructed an energy function E according to the above computational theory. In this formula, i and j denote the logitudinal and the horizontal suffix of the slender rectangular image,respectively, V_{ij} is an activation value at the (i,j) pixel, d(|j-j'|) expresses the distance between the (i,j) pixel and the (i',j') pixel, V^0_{ij} is the value of initial edge map, and l(i,j) denotes the distance between the (i,j) pixel and the center of the column.

$$E = E_a + E_b + E_c + E_d + E_e + E_f$$

$$E_a = \frac{A}{2} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \sum_{j \neq j'} V_{ij} V_{ij'}$$

$$E_b = \frac{B}{2} \sum_{i=0}^{N-1} \left(\sum_{j=0}^{M-1} V_{ij} - 1 \right)^2$$

$$E_c = \frac{C}{2} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \sum_{j'=j-\frac{M}{2}}^{j+\frac{M}{2}} d(|j-j'|) V_{ij} \left(V_{i+1\, j'} + V_{i-1\, j'} \right)$$

$$E_d = -D \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} V^0_{ij} V_{ij}$$

$$E_e = -E \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} V_{ij}$$

$$E_f = F \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} l(i,j) V_{ij}$$

The E_a and E_b are used in accordance with (C-1), E_c with (C-2), E_d with (C-3), E_f with (C-4) of above computational theory, and E_e is an offset of the energy.

We use the ordinary Hopfield network process to find the minimum energy configuration with the following recursive equations, where τ is a relaxation constant and μ_0 is a parameter of the sigmoid function.

$$\frac{du_{ij}}{dt} = -\frac{u_i}{\tau} - \frac{dE}{dV_{ij}}$$

$$V_{ij} = \frac{1}{2} \left(1 + \tanh \left(\frac{u_{ij}}{\mu_0} \right) \right)$$

In this calculatoin, the initial values are set to be equal to the initial edge map and the cyclic boundary condition in the column direction is used.

Search for the coefficients using the small test images: To decide the set of coefficient, we selected a set of fundamental edge patterns which expresses most of the edge pattern. To obtain a set of coefficient which favor a desired pattern as a minimum set, we prepared a desired pattern and two compared patterns for each initial edge pattern. We then searched for the set of coefficients which satisfy the following conditions.

(S-1) Desired patterns have the least energy among the four patterns.

(S-2) Desired patterns are located at the point of local minimum energy.

(S-3) When the Hopfield network is applied, the initial patterns move and converge into the desired patterns.

The fundamental set of patterns are shown in **FIG.1.** We obtained the following coefficient set.

(A, B, C, D, E, F) = (7, 7, 1, 5, 1, 3)

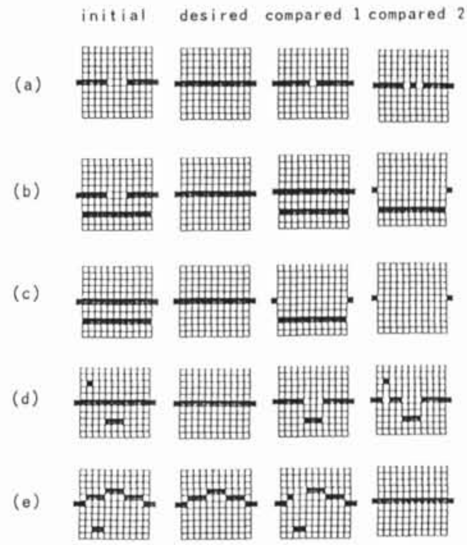

Fig.1 A set of fundamental patterns used to search for coefficients of the energy function

Resolution scaling of the coefficient: We scaled the coefficients in accordance with the following assumptions.

(R-1) Under the same energy function coefficients, different edge patterns converge and contours can be obtained if they have the same resolution or the same pixel-size.

(R-2) We can define an energy function for a continuous image which represents the fine resolution limit.

(R-3) Energy functions of the finite resolution can be seen as approximations of the energy function of the infinite resolution.

(R-4) The width of the contour is one pixel for each resolution edge pattern.

(R-5) Initial edge patterns also have a one-pixel-width.

Under these assumptions, each coefficient's dependency on size can be calculated as follows.

$A \propto N^{-1}$, $B \propto N^{-1}$, $C \propto K^{-1}$, $D \propto N^{-1}$,
$E \propto N^{-1}$, $F \propto (NM)^{-1}$

In these formulae, N is a column number, and M is a row number. K is a number between M and N×M.

We can see these scaling relationships by numerically calculating each energy term. In **FIG.2**, coefficients of 11 × 11 pixel images and 44 × 33 pixel images are compared.

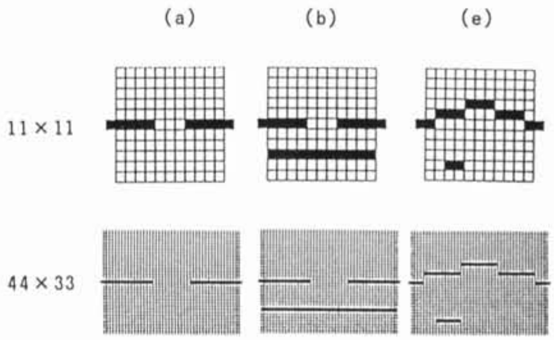

image	term	(a)	(b)	(c)
11×11	Ea	0	16	4
	Eb	3	8	2
	Ec	0	90	48
	Ed	8	19	13
	Ee	8	19	13
	Ef	0	33	20
44×33	Ea	0	64	16
	Eb	12	32	8
	Ec	0	1134	504
	Ed	32	76	52
	Ee	32	76	52
	Ef	0	396	240

Fig.2 Some edge patterns shown with two different resolutions. The chart below shows values of each energy term without coefficeients.

EXPERIMENTAL RESULTS

We applied the algorithm on the image shown in **FIG.3** after Gaussian smoothing. The experiment conditions and parameters are shown below.

Image size: 720 × 576 pixels, 24 bit colors.

Specified guide points: 60, (the total guide contour length became about 1786 pixels long)

Width of the belt: 10 pixels long (Size of the belt-like image became 2400 × 41 pixels after the resampling(**FIG.4**).)

In this experiment, we took zero-crossing of the image. To neglect minute segments of zero-crossing, we made a moving thresholding of 41 pixels wide (**FIG.5**). This belt-like image was divided into small images at the guide points, and their typical length is about 30 pixels. The result of applying our algorithm is shown in **FIG.6** and the final result is shown in **FIG.7**. In this experiment, coefficients are modified according to the scaling relationships. Furthermore, an added constraint is that the contour should be located on the specified guide points at the far right and far left columns. These guide points coincide with the rough position stated in the outline of the process.

Fig.3 The experimental image(720*576, 24 bit full-color)

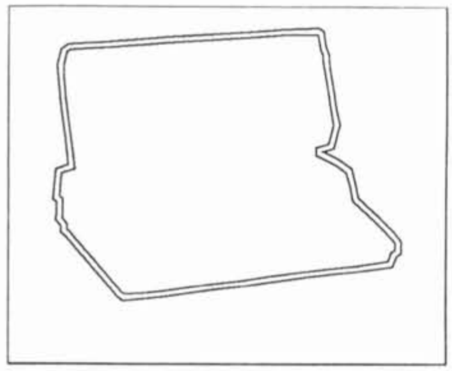

Fig.4 Belt-like region along the specified guide points

As you can see in **FIG.6**, most of the contour is extracted correctly. But, we could not eliminate some small segment which are not on the desired contour. These are so narrow that they cannot be seen easily in the reconstructed image (FIG.7).

DISCUSSIONS

(1) **Computational theory**: We followed Marr's theory of stereopsis in constructing the computational theory. At first, we thought that only three constraints (from (C-1) to (C-3)) were necessary. However, we added (C-4) because we could not discriminate two parallel zero-crossing segments using only these three constraints. (C-4) is not the only possible constraint that could be added, but it is very practical.

(2) **Energy function**: We considered a lot of variations of the energy function, such as continuous and discrete variables, boundary conditions, initial

conditions, and the form of the energy function itself. Although we could express (C-1) and (C-3) by simply imitating Hopfield and Tank's work on the travelling salesman problem and Marr's theory of stereopsis, we could not satisfactorily determine E_c in order to express (C-2). This caused a lot of trouble. For example, some E_c's we tried made the contour fat, failed to connect the long segment that were apart, etc. The form of E_c we adopted in this work is a result of a compromise. Generally speaking, E_c's of (C-2) tend to be so weak that the contours do not connect.

(3) **Search for the coefficients**: Our search for the coefficients of the energy function was done with a limited set of small test images. Of course, there are a lot of edge patterns which cannot be expressed with the combination of our small test images. But we believe that our treatment is sufficient because even if the perfect coefficients are found they still cannot avoid being trapped in a local minimums.

(4) **Scaling relationship**: As stated in the INTRODUCTION, we want a size-independent energy function. Our assumptions (R-1) - (R-5) are rather strong. These assumptions have to be modified when we adopt derivatives as edge maps. Furthermore, edges must be sharp enough. However it must be mentioned that for some cases when scaled energy does not result in the correct contour, there is sometimes a different coefficient that can extract correct result for only part of the image.

(5) **Comparison with SNAKE**: SNAKE[5] is a very successful active contour model. Like SNAKE, our work minimizes the energy function and needs some guidance. However, SNAKE is a controlled continuity spline and our work uses a two dimensional pixel array. Although, as argued in (2) , it is very difficult for us to cope with (C-2), SNAKE always brings about a continuous contour. Still, we have to determine which approach is more likely to experience local minimum traps.

(6) We believe human-guided contour extraction techniques will become more important. Not only examining the problems stated above, we have to consider how to use other imformation such as color to develop a better algorithm.

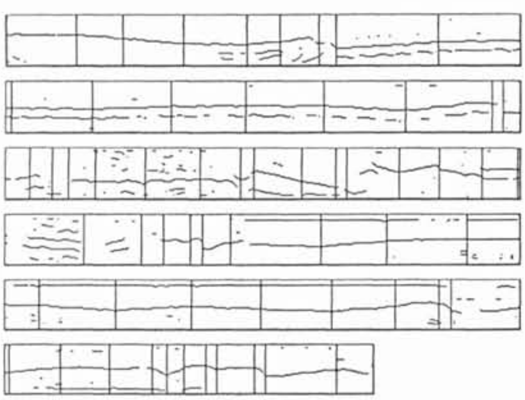

Fig.5 Zero-crossing image of the stretched belt-like region

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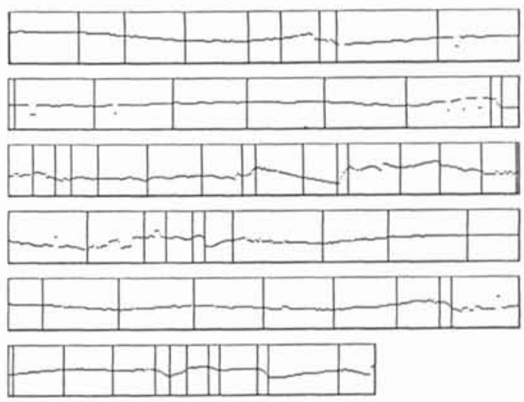

Fig.6 Result of applying the Hopfield network

Fig.7 Final result made by reconstructing the results of **Fig.6**