



A Proposed Method for Contour Extraction of an Image Based On Self-Affine Mapping System by Fractal Coding

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ABSTRACT

A self-affine mapping system instead of the energy minimization procedure is used to approach and fit the roughly drawn line to the object contour. The self-affine map's parameters are detected by analyzing the block wise self-similarity of a gray-scale image using an algorithm in fractal encoding techniques. The edges are attracting mapping points in self-affine mapping is utilized in the proposed method. The proposed method accurately produces smooth curves sharp corners and to extract both distinct edges and blurred edges. The large gaps between the hand-drawn line and the contour can be fitted well by our proposed method and algorithms. In this method block size is progressively decreased. These procedures reduce the time required for drawing contours by hands. As a result, highly accurate contours were extracted in our proposed method.

Keywords: *Contour Extraction, Fractals coding, Self-Affine Snake, Image segmentation, LIFS.*

1. INTRODUCTION

The self-affine mapping system (SAMS) was typically used for producing fractal figures [1], [2] and fractal image coding [3]. A self-affine mapping system which has conventionally been used to produce fractal images is used to fit rough lines to contours. The contours extraction of objects in an image has been investigated actively as it is a significant technology in, image searching, image storing, image editing, image recognition, and other image processing procedures. We often used to overcome this problem is that the line is first drawn roughly near the contour and then it is fitted automatically to the contour. An active contour model called the snake model has been investigated widely as a contour fitting method [6] – [8]. In the snake method, an energy function is defined, according to continuity and smoothness of contour line and image features. The object contour is extracted by minimizing the energy function. Even though the roughly drawn line is fairly distant from the object contour, the line is able to be fitted to the contour in an ideal case, the object contour is formed by distinct edges and the background is almost flat. A new fitting method which provides highly accurate contours is proposed in this paper. The concept of our method is quite different from that of the snake method. A self-affine mapping system instead of the energy minimization procedure is used to approach and fit the roughly drawn line to the object contour. The contractive self-affine mapping system has been used to produce fractal figures [9], [1]. We use it for object contour extraction in this paper. The self-affine map's parameters are detected by analyzing the block wise self-similarity of a gray scale image using a simplified algorithm in fractal encoding [1], [10]. We showed that edges attract mapping points during iteration of the map when the mapping points are initially set near the edges. The object contour is extracted as a self-similar curve instead of a smooth curve. The proposed

proposed a method for demand highly accurate contours, such as object-based composition, mixing, and editing. The contour of objects image is extracted, the background image outside the object can be replaced by another image or a composite image can be made with other objects but in MPEG-4, the international standard of moving picture coding, includes the arbitrary shape coding [4] which can be utilized for object-based composition. Object contours extraction needs are becoming more exacting in image communication and storage [5]. It takes much time and effort to draw an accurate contour by hand. One solution method can extract sharp corners since they have the self-similarity. It is shown that the mapping system extracted both distinct and blurred contours of objects, both sharp corners and smooth curves. This attraction phenomenon is also utilized in the method proposed here, and the contour is obtained as an attractor of the mapping system [12]. As a result, highly accurate contours were extracted. It is also shown that even large gaps between hand-drawn lines and contours can be fitted well by the recursive procedure of the proposed algorithm, in which the block size is progressively decreased [13], [11]. The rest of the paper arranged thus: section 2 presents Overview of Self-Affine Mapping System, section 3 Presents Overview of Self-Affine Snake Model, section 4 Presents Digital Image Processing Using Self-Affine Mapping Systems section 5 presents Our Proposed Contour Extraction Methods, section 6 presents Experimental Result for Contour Extraction, Compare with Snake Models, and Conclusions presents section 7 and section 8 and last section 9 presents references.

2. OVERVIEW OF SELF-AFFINE MAPPING SYSTEM

Consider an image having the support $G \subset \mathbb{R}^2$ with the intensity $I(x)$ for all $x=(x,y) \in G$. The contractive self-

affine map m with the domain $M \subset G$ is defined as follows:

$$x_w = m(x) = r(x - \bar{x}_M) + \bar{x}_W, \quad r > 1 \dots (1)$$

Where \bar{x}_M and \bar{x}_W are the center points of the domains M and W respectively, and we have:

$$\bar{x}_W = \bar{x}_M + \tau \dots (2)$$

In other word, Equation (1) translates M by the vector $\tau = (s, t)$ and contracts it by the coefficient r to make the domain $W = m(M)$ as illustrated in Fig. 1. A contractive self-affine model is defined by $\{M, m, u\}$ where:

$$u(z) = pz + q, \quad z = I(x_w), \quad 0 \leq p \leq 1 \dots (3)$$

In order to maintain the self-similarity conditions, the identity map is usually used for u (i.e. $p=1$ and $q=0$). Furthermore, the scaling coefficient r is usually constant to simplify computations.

Similarly, an expanding self-affine map is defined by $\{W, \omega, v\}$

where $\omega = m^{-1}$ and $v = u^{-1}$ with $r > 1$. The inverse of each contractive self-affine map is an expanding self-affine map and vice versa which means that:

$$x_w = w(x) = 1/r(x - \bar{x}_W) + \bar{x}_M, \dots (4)$$

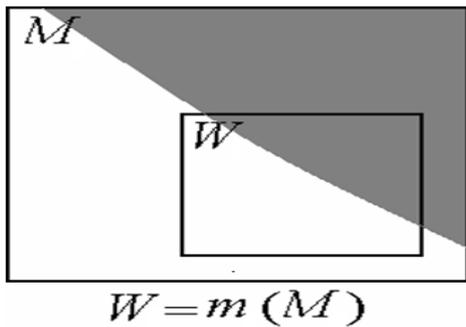


Fig. 1: A contractive self-affine map

The process of extracting self-affine maps includes two steps. First, some domains (M or W) are allocated. The domain allocation method depends on the application of self-affine model. Then, for each self-affine map, the matching algorithm changes the value of one parameter in every step and subsequently, the following matching cost is evaluated [1].

$$\Psi_W(\tau) = \iint_{x \in W} \{I(x) - I(x_m)\}^2 dx dy \dots (5)$$

Therefore

$$\Psi_M(\tau) = 1/r^2 \Psi_W(\tau) \dots (8)$$

In the above equation, the coefficient $1/r^2$ is constant, i.e. both Ψ_W and Ψ_M have the same optimums. Fig. 2 shows that a self-affine model with square domains of size $K \times K$. As shown, the texture in each larger block (M) is almost similar to that in the corresponding smaller block W .

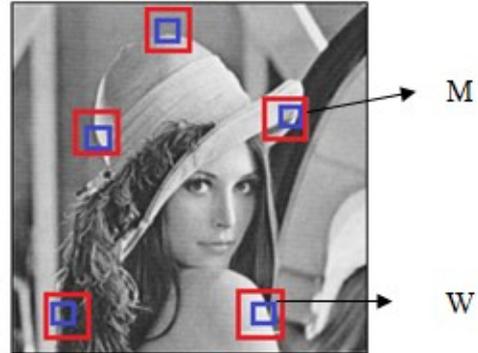


Fig. 2: A self-affine model large (M) & small block (W)

3. OVERVIEW OF SELF-AFFINE SNAKE MODEL

In this paper we discuss Self-affine snake (SAS) model very briefly, the comparison between snake model and our proposed method presents section 7. It is a remarkable parametric active contour which recently proposed by the authors [17].

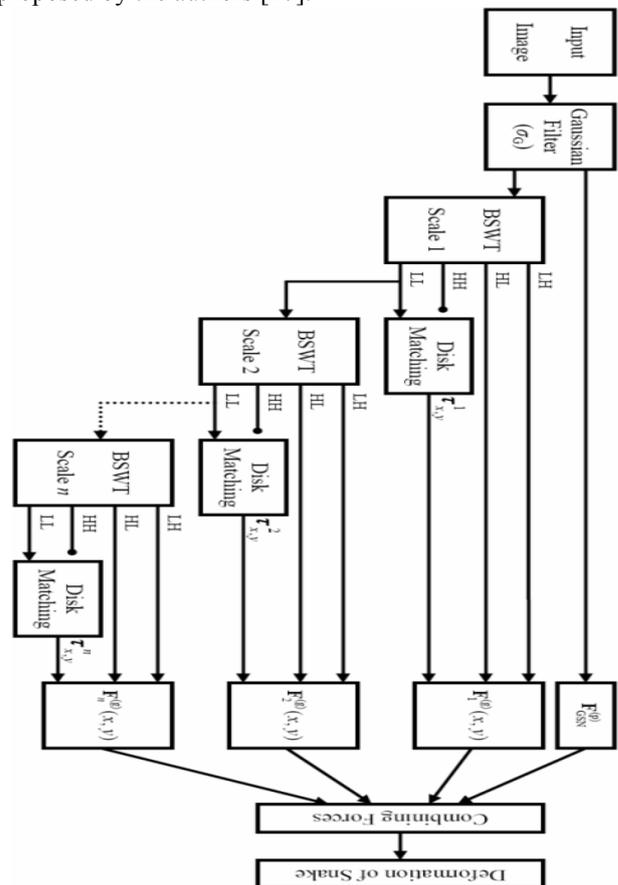


Fig. 3: Shows Self-affine snake model



In this approach, the wavelet transform and self-affine mapping system were combined to compute a global force field for parametric active contours. Fig 3 shown the snake self-affine model. This model includes six phases as follows:

- (a) Gaussian filtering
- (b) Computing wavelet coefficients by using biorthogonal spline wavelets [18]
- (c) Extracting optimal self-affine maps in each wavelet scale
- (d) Computing self-affine sub-forces in each scale
- (e) Combining sub-forces to obtain self-affine force field and
- (f) Snake deformation using dynamic force formulation [19].

In SAS, the disk matching algorithm was used for extracting optimal self-affine maps [17]. This method finds the optimal translation vector which minimizes the cost function Ψ_W of equation (5).

4. DIGITAL IMAGE PROCESSING USING SELF-AFFINE MAPPING SYSTEM

Some image representation methods using the self-affine map parameterized by the self-affine model have been proposed as applications. These include fractal segmentation [11], [14], edge detection [11], and compression with pixel chaining decoding [14], [15]. In all of these applications, first a self-affine model is extracted and then iteration of the self-affine map is performed. Fractal image coding was originally proposed by Barnsley [16], [17] as a compression method for binary images and was applied to gray scale images by Barnsley and Jacquin [1], [10]. The image is extracted as a self-affine model, using the block matching algorithm with the condition $|p| < 1$, which is needed to decode the image. Usually, a contractive transformation of images called the fractal transformation is used for decoding. The image is obtained as an attractor with the transformation. In another decoding method using self-affine mapping, a map of points in combined. The decoded image is obtained as the set of intensity values which do not diverge as a result of iteration of the map [15]. Some variations of this decoding method are shown in references [14] and [15].

5. OUR PROPOSED CONTOUR EXTRACTION METHODS

We propose a new method for boundary fitting of alpha masks to object contours in which the contour is obtained by calculating the attractor of the self-affine mapping system. A binary image called an alpha mask is made by setting 1 for the pixels inside the line to define them as the foreground and 0 for the other pixels to define them as the background. Our purpose is to fit the boundary

between the foreground and background in the alpha mask to the object contour in the gray scale image. A binary image called an alpha mask is made by setting 1 for the pixels inside the line to define them as the foreground and 0 for the other pixels to define them as the background. Our purpose is to fit the boundary B between the foreground and background in the alpha mask to the object contour in the gray scale image.

Our proposed contour extraction algorithm

Iteration 1: The side length c of W_i is set to c_{max}

Iteration 2: $W_i (i=1, 2, \dots, N)$ are using the allocation C as follows

K is a variable set to 1, the alpha mask is scanned pixel by pixel line by line i.e. top to bottom and left to right etc. The differences between two adjacent pixels, i.e. any pixel having different adjacent pixels so only two adjacent pixels consider it may be adjacent pixel of left side and upper side or it may be right side and lower side pixel occurred. Then that value is not include $W_i (I < k)$ which has been already placed and the value of W_i will add with the centre pixel and the value of K will increase $K+1$.

Iteration 3: Our proposed self – affine mapping is extracted the image contour.

Iteration 4: The self affine mapping S is iterated number of η times to the foreground region of the alpha mask from the iteration 3 . Consider the value

$$\alpha_i = m_i (= w_i^{-1}) \dots\dots\dots (9)$$

$$A_i = M_i (= W_i) \dots\dots\dots (10)$$

The value C is fixed for the equation as

$$C = X_0 \cap \bigcap_{i=1}^I \overline{W}_i \dots\dots\dots (11)$$

to keep the regions where W_i is not placed as they are. Here, X_0 is the foreground region of the initial alpha mask. The procedure of each map S is such that the area of the alpha mask is overwritten with the pixel value 0. The pixel value 1 is set for each pixel $x \in W$, and then the corresponding sampling value at $w_i(x)$ is equal to 1.

$$\bigcup_{i=1}^I W_i \dots\dots\dots (12)$$

Iteration 5. It may be consider as $c = c/2$, for this case the c is smaller than c_{max} , the process is complete else goto iteration 2.

Iteration 6. End of the process, otherwise iteration 1.

Our proposed method satisfy some conditions as Let e is the value small block; c is the value of side length. Then (a) For every m_i are exactly contractive,

(b) The value of e always adjacent to c . And both value e and c are covered by W_i as follows

$$e \subset \bigcup_{i=1}^I W_i \dots\dots\dots (13)$$

$$c \subset \bigcup_{i=1}^I W_i \dots\dots\dots (14)$$

Here the part of c and e are belongs to every W_i . Therefore the equation may describe this way as

$$c \cap W_i \neq \phi \dots\dots\dots (15)$$

$$\text{And } e \cap W_i \neq \phi \dots\dots\dots (16)$$

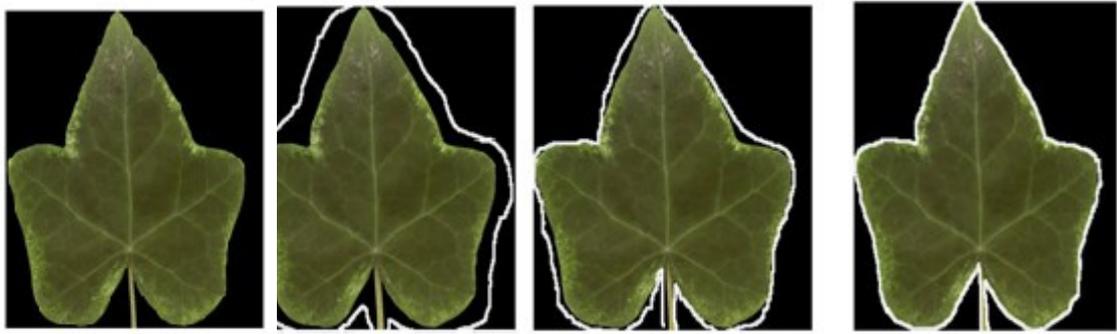
Here W allocation method C is used while equation (15) and (16) are satisfied. Again after larger value c is increase the probability while satisfied the equations (14) and (15). Furthermore W_i is set centered on a pixel of e and the side

length of W_i must be more than square the length of the gap between e and c .

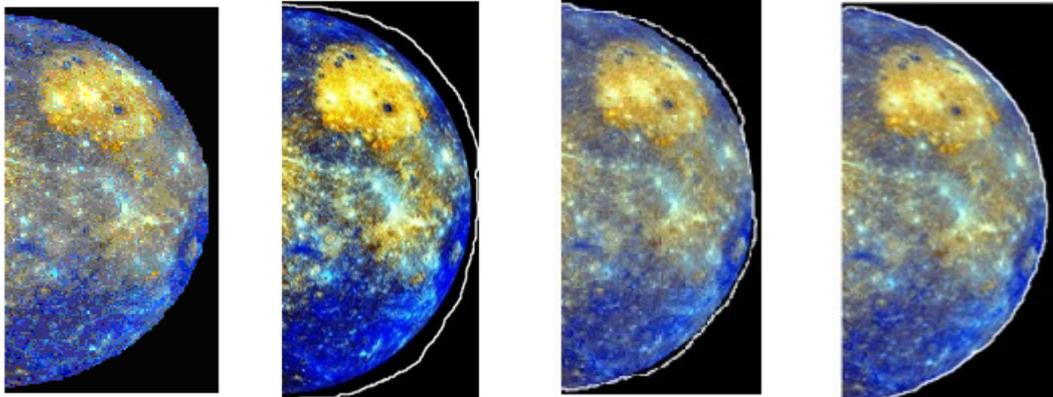
(c) The value of c is always equal to the invariant set of S , if $c \cap W_i$ is similar to $c \cap M_i$ for every i , c is equal to the variant set of S .

6. EXPERIMENTAL RESULTS FOR CONTOUR EXTRACTION

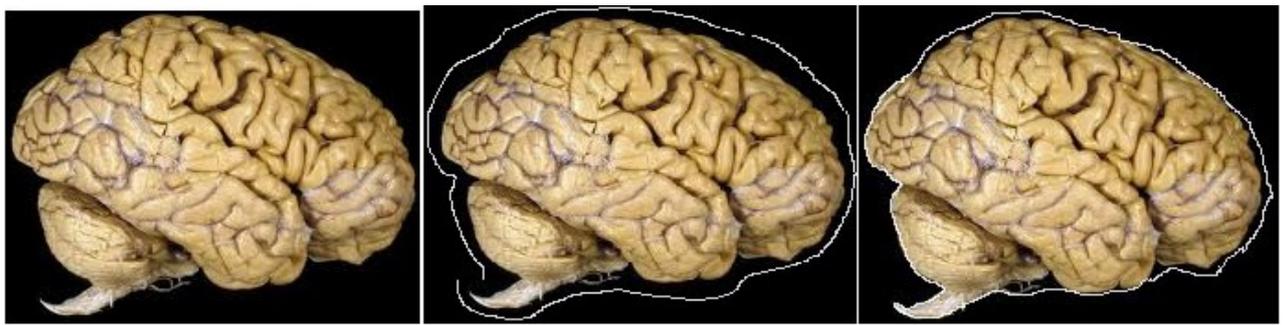
From the experimental result the block size of M_i was set to double that of W_i ($r = 2$), and v was set as the identity map ($p=1, q=0$). From the fig. 1 and fig.2. it can be seen that the texture of W (smaller block) is the same as that of larger block), and that the gap between them is half of that in larger block. alpha mask at $w_i(x)$ was detected as the majority value, 0 or 1, of the four pixels around the sampling point. If the numbers of 0s and 1s were equal to each other, the sampling value was set to 0.



(a) (b) (c) (d)



(e) (f) (g) (h)



(i) (j) (k)



Fig.4. Shows Original images, rough contour drawn by hand, Snake method, our proposed contour extraction method

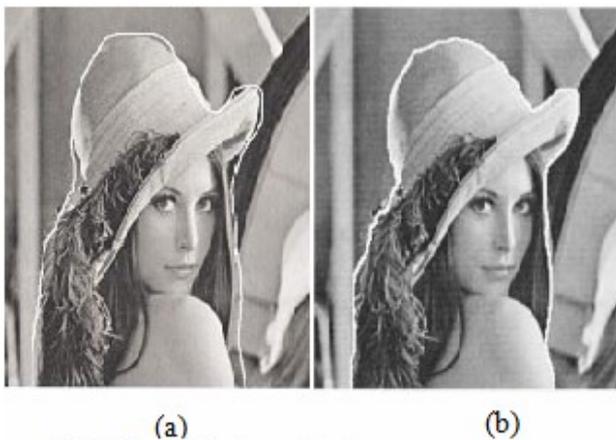


Fig 5. Shows Snake method, our proposed contour extraction method

The contour of the test image is shown in fig. 4. (d, h, l) and fig.5. (b) was extracted using the proposed method. The white lines shown in Fig. 4 (b, f, j and n) are roughly drawn by hand. And fig. 4. (c, g, k) and fig.5(a) are Shown the contour extraction image using Snake method, the original images are shown in fig. 4. (a, e, I, m) . The corners and details of the contours were produced by smaller block sizes using our proposed method fig. 4 (d, h, l) and fig.5 (b) shown the corner and details of the contour extraction images. The sharp corners were also extracted accurately in the full search using our proposed method. In the block matching step, the sum of the mean absolute distances of the three colour components was used as the measure.

7. COMPARE WITH SNAKE MODELS

We proposed a self-affine model as an object contour model in this paper. A contour model is usually required for the extraction of edges as object contours. There are usually many edges of texture and noise other than in both the foreground and the background except in ideal texture-free and noise-free images. For misextraction of the texture or noise as a contour is avoidable if a proper

model is used as the constraint of the contour line. Continuity and smoothness are used as energy function constraints in the snake method [6], [7]. This model works well for smooth curved contours. However, sharp corners of contours are difficult to extract without making the weight coefficient for smoothness small. Neglecting the smoothness may introduce misextraction of texture or noise. The experimental results of contour extraction by the snake method are shown in Fig.4. (c, g, k) and fig.5 (a). We implemented the time-delayed discrete dynamic programming algorithm [7], and parameters including the weight coefficients for continuity, smoothness and edge energy in the energy function were optimized for each image. Images on the Fig. 4. (a, e, I, m) are the initial states, and the rough shape was drawn by hand shown in fig. . 4 (b, f, j and n) . The extracted contour by the snake method is shown on the fig. 4. (c, g, k) and fig.5(a), images could not be extracted using snake method. Block matching required much time in the case of the proposed method, and the snake method needed much processing, including smoothing of the original image and the edge energy image, before the minimization process. The self-affine model based on block wise self-similarity can match the contour corners as long as each block contains only a single corner, because a single corner shape has self-similarity. The blurred contour of the cloud was extracted well by the proposed method as shown in Fig. . 4 (d, h, l) and fig.5 (b). However the snake method, could not extract the contour since the absolute value of the edge energy was so small that the line passed through the contour in the process of minimizing the energy function. The main weakness of our proposed method compared with the snake method is that the applicable contour gap is bounded with the block size. For this way the gap is too large, a combination of the two methods, in which the snake method is applied first and then the proposed method is applied, would provide a good result.

8. CONCLUSIONS

The self-affine map was defined as an extension of LIFS, with the applicability of the mapping

system extending to image processing including, image compression, edge detection, and image segmentation. Our proposed methods for fitting of the alpha mask boundary to an image contour. The proposed method accurately produce smooth curves, sharp corners and to extract both distinct edges and blurred edges. It is also shown that large gaps between the hands draw line and the contour can be fitted well by our proposed algorithms. These methods block size is progressively decreased. It reduces the time required for drawing contour by hand. Many more applications related to image edge regions and contours to be developed using our proposed methods.

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