

A GENETIC ALGORITHM BASED IMAGE SEGMENTATION FOR IMAGE ANALYSIS

Miki Haseyama, Masateru Kumagai and Hideo Kitajima

School of Engineering, Hokkaido University,
Sapporo 060, JAPAN

Tel/Fax: +81 11 7066077

{mikich, kumagai, kitajima}@media.eng.hokudai.ac.jp

ABSTRACT

In this paper a new genetic algorithm (GA) based image segmentation method is proposed for image analysis. This method using a mean square error (MSE) based criterion can segment an image into some regions, while estimating a suitable region representation. The criterion is defined as MSE caused by interpolating each region of an observed image with a parametric model. Since the criterion is expressed with not only the parameters of the model but also shape and location of the regions, the criterion can not be easily minimized by the usual optimization methods, the proposed method minimizes the criterion by a GA. The proposed method also includes a processor to eliminate fragile regions with the Markov random field (MRF) model. Though the thresholds of the existent methods negatively affect image segmentation results; since no thresholds are required in the proposed method, it segments images more accurately than the existent methods.

1. INTRODUCTION

Several image segmentation methods have been proposed [4]. They usually use thresholds to decide whether two pixels are in the same region [5]. However, the thresholds negatively affect the image segmentation results frequently in accuracy. The users have to set up their values carefully for these methods.

Reference [5] can select appropriate parameters to segment images by a genetic algorithm (GA). This method selects the suitable parameters by utilizing multiple images of the same target with a genetic learning system. However, because it segments images by requiring multiple frames of the same target, the method can not be used for analysis of the images if only one image is observed.

We propose a GA based image segmentation method which formulates the segmentation problem by minimizing a criterion represented by a mean square error (MSE). The MSE is expressed with not only the parameters for representation of each region of an image, but also the shape and the location of the regions. As a result, the criterion can not be easily minimized by the usual optimization methods, such as the gradient estimation method, etc. In order to minimize the criterion, a GA is introduced.

In contrast with the existent methods, the proposed method can segment an image with only the target image

itself. It does not require any thresholds, and every parameter is appropriately computed in the GA processing. Therefore, the image segmentation results can be obtained more accurately.

Our method also includes a processor to eliminate fragile regions [1] with the Markov random field (MRF) model [7]. Because of the introduction of the MRF model, the GA processing can search for the optimal segmentation result without being caught by local minima.

The criterion for image segmentation is defined in Section 2. The image segmentation method using a GA is presented in Section 3. The capability of the method is demonstrated on a set of real images in Section 4. Since this method can segment images while estimating the region representation, it can be utilized for image analysis.

2. A CRITERION FOR IMAGE SEGMENTATION

An observed digital image is described as $f(x, y)$ ($x = 1, \dots, N$, $y = 1, \dots, M$), one of its segmentation results is f , its regions are denoted by R_i ($i = 1, \dots, K$). The pixels in a region R_k are interpolated as

$$\hat{f}_{R_k}^{opt}(x, y) \triangleq \sum_{i=0}^P \sum_{j=0}^{P-i} p_{R_k}^{ij} x^i y^j, \quad (1)$$

where as

$$\hat{f}_{R_k}(x, y) \triangleq \sum_{i=0}^P \sum_{j=0}^{P-i} p_{R_k}^{ij'} x^i y^j,$$

$p_{R_k}^{ij}$ is $p_{R_k}^{ij'}$ which minimizes

$$\sum_{(x,y) \in R_k} (f(x, y) - \hat{f}_{R_k}(x, y))^2.$$

In the proposed method, the accuracy is defined with the MSE of an image segmentation result f as:

$$MSE(f) \triangleq \frac{1}{MN} \sum_{k=1}^K \sum_{(x,y) \in R_k} (f(x, y) - \hat{f}_{R_k}^{opt}(x, y))^2. \quad (2)$$

Consequently, the optimal segmented image is acquired when the MSE is minimum at the number of a region K .

3. GA BASED IMAGE SEGMENTATION METHOD

3.1. Design of the GA

3.1.1. Chromosome and Its Representation

A chromosome in our method is a segmented image, that is an image segmentation result, and the structure of the chromosome is shown in Fig. 1. The genes from $((k-1)\{\frac{(P+1)(P+2)}{2} + 3\} + 1)$ th to $(k\{\frac{(P+1)(P+2)}{2} + 3\})$ th of the chromosome represent the region R_k . Each gene is defined as follows:

i) x_k, y_k

The coordinate (x_k, y_k) is a point to start the simple region growing method for generating the region R_k , which controls the region growing process with average contrast.

ii) θ_{g_k}

A threshold of average contrast between R_k and its neighbor for the simple region growing.

iii) $\hat{p}_{R_k}^{00} \cdots \hat{p}_{R_k}^{P0}$

A set of parameters of $\hat{f}_{R_k}(x, y)$.

The above genes are not enough for our GA processing, because after segmentation with them areas where are not yet segmented still remain. Therefore, the areas are segmented by the simple region growing method by using the following genes.

iv) d_i

The direction in which the simple region growing generates the region R_k .

v) θ_u

A threshold of average contrast for the simple region growing in the not-segmented area.

Further, the segmented image by the above genes is adapted to the MRF model[7][8] for elimination of fragile regions with the following parameters.

vi) β

A parameter for the MRF model defined in [7].

vii) l

A number of times for adapting the segmented images to the MRF model.

By using the above genes, a chromosome is obtained uniquely.

3.1.2. Fitness of the Chromosomes

The fitness of a chromosome f is defined as follows:

$$Fitness(f) \triangleq -MSE(f) - F(N(f)) \quad (3)$$

where $N(f)$ is the number of regions of the segmented image f , and F is a function of $N(f)$. The function F is necessary to distinguish chromosomes with the same fitness but the different number of regions. It is defined as

$$F(N(f)) \triangleq C_1 (N(f) - C_2 K)^2, \quad (4)$$

where C_1 and C_2 are constants.

3.2. Procedures of the Proposed Method

Procedure1: Creation of the initial population

The initial population of chromosomes is randomly generated. However, the genes x_k and y_k are randomly selected in the area except already segmented regions: $R_1, \dots, R_{k-1}$.

Procedures2: Computation of fitness

The fitness of each chromosome is computed from Eq. (3).

Procedures3: Reproduction

We use roulette wheel selection which is conducted by spinning a biased roulette wheel sized in proportion to the fitness of each chromosome, and the elitist replacement whereby the best fitness chromosome is copied into the next generation[3].

Procedure4: Crossover

Two chromosomes selected by the reproduction are called *Parent1* and *Parent2*. We apply two-point crossover to the genes d_i, θ_u, β , and l . Each gene of *Parent1* and *Parent2* is coded to binary for the crossover in the same locus. Its crossing points are selected at random.

For the other genes $x_k, y_k, \hat{p}_{R_k}^{00}, \hat{p}_{R_k}^{01}, \dots, \hat{p}_{R_k}^{0P}, \dots, \hat{p}_{R_k}^{P0}$ ($k = 1, \dots, K$), the crossover is performed as follows: First, we select the region R_{k_2} of *Parent2* nearest to R_{k_1} of *Parent1*. Second we apply two-point crossover to the binary-coded genes $\hat{p}_{R_{k_1}}^{ij}$ of *Parent1* and $\hat{p}_{R_{k_2}}^{ij}$ of *Parent2*.

With this crossover operation, the offsprings can inherit the characteristics of their parents.

Procedures5: Application of the MRF model to the chromosomes

The chromosomes obtained in **Procedure4** are applied to the MRF model with parameters β and l .

Procedure6: Mutation

Each bit of the binary-coded genes is varied according to a mutation probability.

Procedure7: Termination of the GA processing

If the condition to terminate is satisfied, we terminate the GA processing, otherwise we repeat **Procedure2** – **Procedure6**.

4. SIMULATION RESULTS

This section shows the performance of our method on white noise-added images by some simulations.

The image in Fig. 2(a) is a 256×256 image represented with 256 gray levels and has 75 regions, and its boundary lines are shown in Fig. 2 (b). A Gaussian noise is added to each region with a different variance.

The parameters for the experiments are shown in Table 1. In the table, the population size, the mutation probability, and the termination rule are necessary for the ordinary

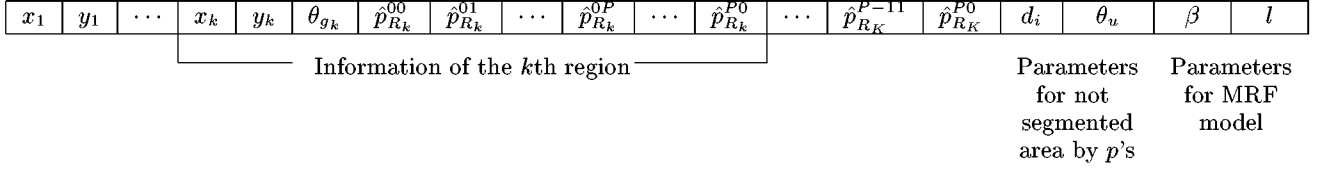


Figure 1: A chromosome

Table 1: Parameters used for experiments.

Population size	100
Mutaion probability	3%
Termination rule	No evolution for 30 generations
Number of regions (K)	75
Parameters (θ_{g_k}, θ_u)	0~30.0 (12-bit quantization)
MRF parameter l	0~10
MRF parameter β	0.0~10.0 (12-bit quantization)
C_1 in Eq. (4)	0.1
C_2 in Eq. (4)	0.95

GA processing. They are fixed at large numbers for the purpose of avoiding the local minima in our experiments. The other parameters introduced to the proposed method denoted in Sections 3 and 2, are given as:

- i) C_1 and C_2 in Eq. (4)

C_1 is selected in $0.03 \leq C_1 \leq 0.2$, and C_2 is selected in $0.8 \leq C_2 \leq 0.97$. The proposed method is not sensitive in these ranges to the parameters C_1 and C_2 .

- ii) Ranges of θ_{g_k} and θ_u

These parameters need to be binary-coded for the crossover operation. Then they are quantized in the ranges. The ranges are set at wider values than usual, because they can be applied for segmentation of any images.

- iii) Ranges of β and l

By the same reason of the above, the ranges for their quantization are set at wider values than usual. For example, the range of β is twice as large as the same shown in [8].

Each of those six parameters can be set independently of characteristics of the reference image. Therefore, they can be used for segmenting the other images.

Further, the number of the regions K is set at 75, and the parameter P in Eq. (1) is 2.

The parametric model of the pixels in each region is unknown. The proposed method can estimate the parametric model appropriately while segmenting the images. Therefore, it can be used for image analysis.

The image segmentation result by the proposed method is shown in Fig. 2 (c). For comparison, Figs. 2 (d) and (e) show two image segmentation results by the simple region growing method and the method Partition mode test [10], respectively.

In Figs. 2 (c) – (e), the wrongly segmented regions are grayed. The number of the segmented regions and the error that is defined as the ratio of the grayed region to the whole image are shown in Table 2.

Comparing with the other methods, our method yields (1) the number of segmented regions that is the closest to the true region number, and (2) the smallest error rate.

5. CONCLUSIONS

In this paper, a new genetic algorithm based image segmentation method is proposed. The method segments an image based on the criterion using the MSE. It also includes a processor to eliminate fragile regions with the MRF model. Furthermore, it segments an image by the optimization without using any thresholds, so that it can provide more accurate segmentation results than the existent methods. Since this method segment an image while estimates the region representation, it can be utilized for image analysis.

The method yields better segmentation results comparing to some existent methods.

6. REFERENCES

- [1] Kocher M. and Kunt M. "A contour-texture approach to picture coding". *Proceedings of International Conference Acoustics, Speech and Signal Processing*, pages 436-440. May, 1982.

Table 2: Experimental Results

	Number of Regions	Error(%)
Fig. 2(c) (Proposed Method)	75	1.9
Fig. 2(d) (Simple Region Growing)	868	20.9
Fig. 2(e) (Ref. [10])	82	12.6

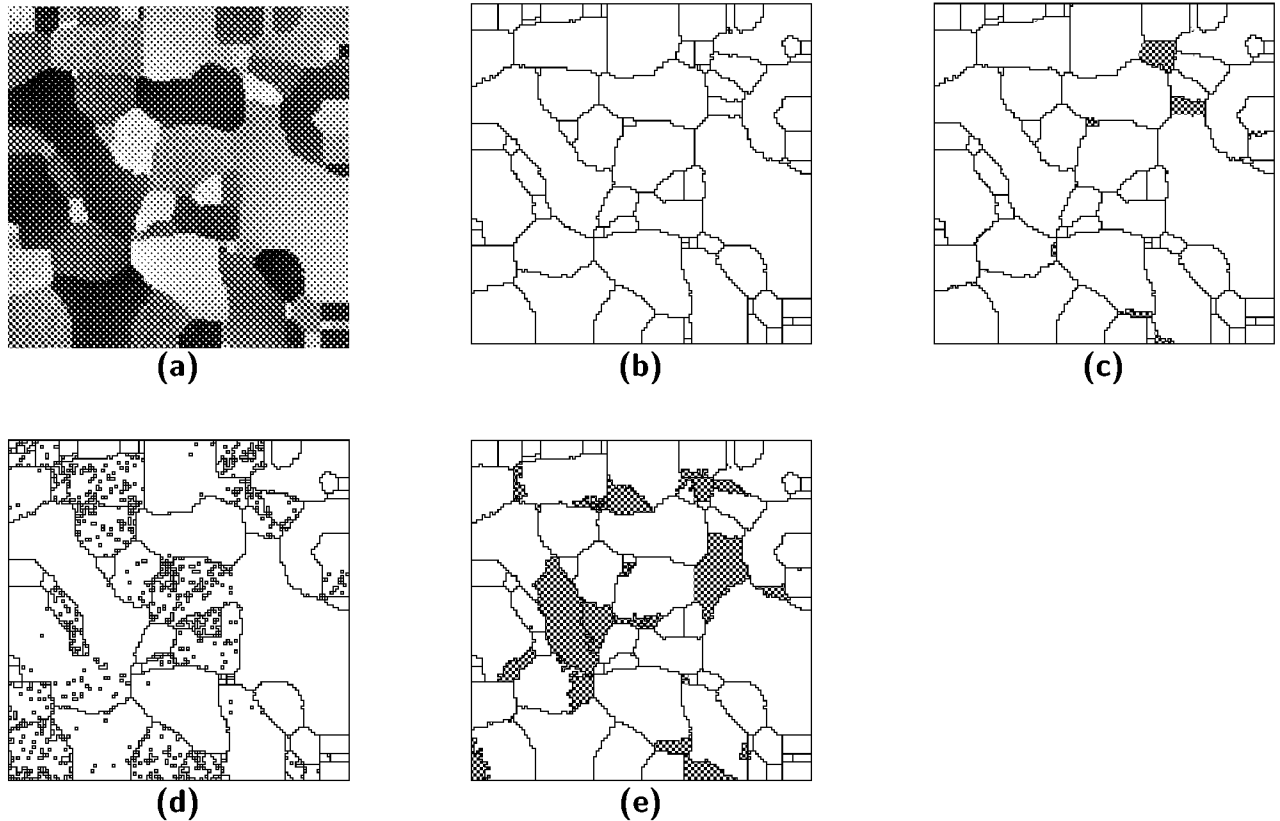


Figure 2: Image Segmentation Results. (a) A test image (75 regions). (b) Boundary lines of (a). (c) A segmentation result of the proposed method. (d) A segmentation result of the simple region growing method (the threshold 13). (e) A result of [10] ($T_1=15, T_2=20, T_3=10$; These thresholds are defined in [10]).

- [2] Kunt M. "Second-Generation Image-Coding Techniques". *The IEEE Proceedings*, Vol. 73, No. 4, pages 560-563. April, 1985.
- [3] Goldberg D. E. *Genetic algorithms in search, optimization, and machine learning*, Addison Wesley Publishing Company, 1989.
- [4] Haralick R. M. and Shapiro L. G. "Image Segmentation Techniques". *Computer Vision, Graphics, and Image Processing* 29, pages 100-132, 1985.
- [5] Bhanu B., Sungkee L., and Ming J. "Adaptive Image Segmentation Using a Genetic Algorithm". *IEEE Trans. on System, Man, and Cybernetics*, Vol. 25, No. 12, pages 1543-1567, 1995.
- [6] Tomita F., Shirai Y., and Tsuji S. "Description of textures by structural analysis". *Proceedings of 6th IJCAI*, Tokyo, pages 884-889, 1979.
- [7] Geman S. and Geman D. "Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images". *IEEE Trans. Pattern Anal. and Mach. Intell.*, PAMI-6, pages 721-741, 1984.
- [8] Yamazaki T., Shirazi M. N., and Noda H. "Data-driven segmentation of noisy images modeled with Markov random fields". *Syst. Comput. Jpn. (USA)*, vol.24, no.10, pages 62-72, 1993.
- [9] Nagao M. and Matsuyama T. "Edge Preserving Smoothing". *CGIP Vol.9* pages 394-407, 1979.
- [10] Suk M.S. and Chung S.M. "A new image segmentation technique based on Partition Mode Test". *Pattern Recognition* 16, pages 469-480, 1983.
- [11] Pitas I. "Optimization and adaptation of discrete-valued digital filter parameters by simulated annealing". *IEEE Trans. Signal Processing*, 42, 4, pages 860-866, April, 1994.