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Contour Extraction of Unlawful Invasion Object Using Bi-phased Genetic Algorithm†

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Abstract

This paper describes the contour extraction technique of the unlawful invasion object to construct a machine vision monitoring system. An active contour model is applied to extract an accurate contour of the object from the image that includes noisy and incomplete information. The minimization problem of the energy function of the active contour model is solved by using the Bi-phased Genetic Algorithm which is a new type of the genetic algorithm. The Bi-phased Genetic Algorithm dynamically uses the exploration and the exploitation properties of the genetic search.

A system of Bi-phased Genetic Algorithm is constructed to achieve the improvement of the contour extraction ability. The system is composed of two genetic search phases to control the exploration and exploitation properties of the genetic search simultaneously. The advantages of the Bi-phased Genetic Algorithm are confirmed through the experiment using several images.

KEY WORDS: (Machine Vision Monitoring System) (Genetic Algorithm) (Active Contour Extraction) (Bi-phased Genetic Algorithm) (Robust Processing)

1. Introduction

The construction of a machine vision monitoring system requires accurate information on the object from the image. The outline configuration of the object is the most important information by which its property can be specified. With the exception of high-quality images from well-controlled environments, the simple edge detectors produce spurious edges because of the problems of noise, occlusions and poor contrast.

An active contour model called Snakes has been proposed by Kass et al.[7], and is regarded as an appropriate technique for contour extraction from noisy and incomplete information. A flexible and deformable spline curve is set as an active contour model, and the energy function is defined on this curve. The minimization procedure of the energy function is a key problem, and many methods have been proposed to solve this minimization problem[1), 7), 12), 15)]. However, these techniques have some disadvantages such as lengthy processing time or instability of the solution. The most serious problem is that all these methods are lacking in robustness to noise. The robustness to noise is one indispensable ability acquired in the machine vision monitoring system. The authors have applied the genetic algorithm(GA) to the active contour model and obtained some promising results[6].

To improve the contour extraction ability, a new type of the genetic algorithm, named Bi-phased Genetic Algorithm(hereafter, BIGA) is proposed. The BIGA is composed of two phases to control the exploration and exploitation properties of the genetic search dynamically. Consideration is given to the parameters of such genetic search phases, and Intermediate Generation(IG) is created to improve GA's local search ability. The processing results by the BIGA are compared with those by other methods, and the advantages of the proposed algorithm is confirmed by several experiments.

The contents of this paper are as follows: An active contour model and related problems of previously used methods for minimizing the energy function are

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explained in section 2. The GA application to an active contour model and the investigation of the parameters of GA are described in section 3. In section 4, the concept of the BIGA is introduced, and the BIGA system is constructed. The experimental evaluation of the proposed algorithm and comparisons with other methods are given in section 5. The conclusion is given in the final section.

2. Active Contour Model and Minimization Methods

2.1 Active Contour Model

An active contour model called Snakes was proposed by Kass et al. to extract the outline of the object from the image. Snakes has an advantage in that the edge information is integrated along the entire length of the curve, providing a large support without including irrelevant information of the image. This advantage allows Snakes to find exact contours which the simple edge detectors could not find[10].

A flexible and deformable spline curve is set as an active contour model, and the energy is defined on this curve. The curve is gradually deformed so that the energy may decrease and, finally, it converges to the contour of the object at the minimum level of the energy. The energy defined on the curve includes the internal spline energy and the external spline energy. The internal spline energy, which depends on the shape and the size of the curve itself, serves to impose a piecewise smoothness constraint. The external energy depending on the image-potential of the object pushes Snakes toward salient image features like lines and edges. The weights of the smoothness and the image force terms in the energy functional can be adjusted for the different behavior. The contour extraction method is reduced to an optimization problem of the energy function as shown in **Eq. 1**:

$$\begin{aligned} E_{Snakes}(\mathbf{v}(s)) &= \int_0^1 \{(E_{int}(\mathbf{v}(s)) + \gamma E_{ext}(\mathbf{v}(s))\} ds \\ E_{int}(\mathbf{v}(s)) &= (\alpha|\mathbf{v}_s(s)|^2 + \beta|\mathbf{v}_{ss}(s)|^2)/2 \\ E_{ext}(\mathbf{v}(s)) &= -\{G_\sigma(\mathbf{v}(s)) * \nabla^2 I(\mathbf{v}(s))\}^2 \\ G_\sigma(\mathbf{v}(s)) &= \exp(-|\mathbf{v}(s)|^2 / 2\pi\sigma^2) \end{aligned} \tag{1}$$

where E_{Snakes}, E_{int} and E_{ext} are the total, the internal and the external energy of the spline curve respectively. $\mathbf{v}(s)$ is the vector of the spline curve on the point $(x(s), y(s))$, and s is the normalized parameter of the curve by its length l. $\mathbf{v}_s(s)$ and $\mathbf{v}_{ss}(s)$ are the 1st and the 2nd differentiation with s, and $I(s)$ is the intensity of the image at the point $(x(s), y(s))$. The constants α, β and γ are the coefficients of the weights for each term, and σ is the standard deviation of the Gaussian function $G_\sigma(\mathbf{v}(s))$. The symbol $*$ denotes the convolution.

2.2 Minimization Methods and Related Problems

A solution for the Snakes is found using variational calculus[7]. The energy terms can be adjusted, and a local minimum solution can be obtained as the iteration of calculation proceeds. Amini et al. pointed out some of the problems in variational calculus, including numerical instability and a tendency for points to bunch up on strong edge portions[1]. They have proposed dynamic programming (namely, open loop DP) for minimizing the energy function and allowing addition of hard constraints to obtain the more desirable behavior of Snakes. However, their method is not exactly formulated, and its start point and end point move apart from each other during the iterations. A greedy method was proposed by Williams et al.[15]. While the algorithm is simple, it is not guaranteed to give an acceptable solution. Ueda et al. have proposed dynamic programming (namely, closed loop DP)[12], and although their algorithm gives suitable solution, its calculation cost is very expensive.

All of the methods mentioned above have the problems, such as their processing time is too much, or they easily lead to a miss-solution depending on the parameters setting. The most serious problem is that those methods are very sensitive to the noise on the image. The GA is applied owing to its superior exploration and exploitation properties to overcome these problems.

3. Genetic Algorithm for Active Contour Model

The GA is an optimization technique that imitates a living thing's evolution in nature system. That is, the following generation is formed by a lot of existence of individuals who have high fitness to the environment in

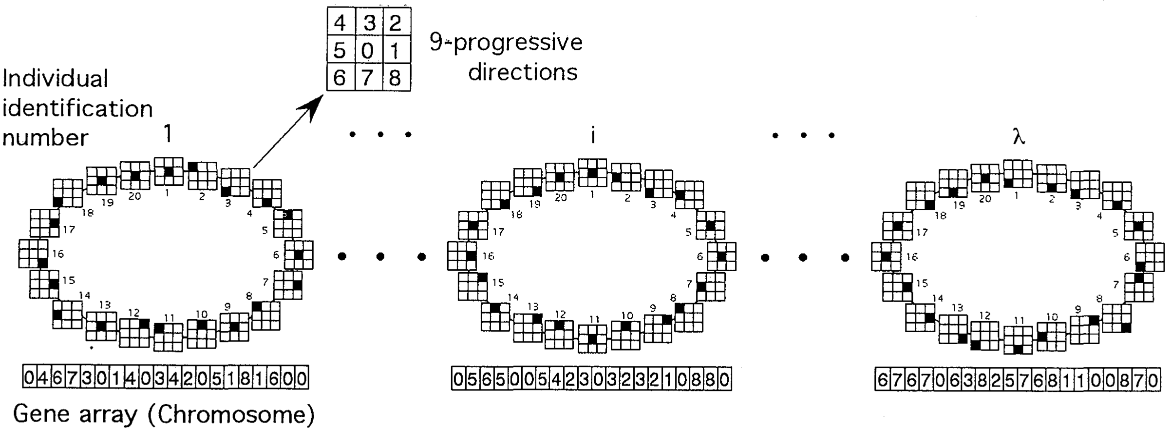

Fig. 1 Active contour model expressed for Genetic Algorithm

current generation. Therefore, when the GA is applied to an optimization problem, the target function of the given problem is taken as the fitness, and the candidate solution is made to correspond to each individual.

3.1 GA Application to Active Contour Model

The GA is used as the method to decide the direction for each point on the active contour curve of a digital image to advance to the next step. Every time a new active contour curve is formed and the optimum direction for each point is decided through calculation of the GA. According to this decision, the deformation is proceeded, and the next new curve is formed. The contour, the border line of the object, is extracted by repeating this operation until it converges to a certain state.

In reality, if we set the direction of each point on the curve to the 9-progressive directions (the 8-neighbors and the present position; here, the square pixel is assumed in the digital image), quite a lot of combinations will generate for all points (n points: the number of Snakes points). l(the number of individuals in the GA) sets are taken from these combinations arbitrarily at first. The example for n=20 is shown in **Fig. 1**, where each set is expressed as the figure rows of the 9-progressive directions.

3.2 Exploration and Exploitation Ability of Genetic Algorithm

The GA is a powerful method for solving multimodal problems. However, at the same time, it is a weak method because of its lack of local search ability[5]. To overcome this weak point of the GA in the application domain of the multimodal function optimization, many researchers have tried to introduce the merits of local search strategies into the GA system[3), 4), 8)]. Although some of them are useful, most of them are too expensive and sacrifice the advantages of the GA . This trade-off problem is caused that their attempts are concentrated on only the improvement of the local search ability.

For the purpose to solve the problem, this paper proposes the BIGA. The BIGA is constructed of two phases, each has the different feature respectively, to give the system both the abilities of local and global search[a)] simultaneously. This can be realized by setting the parameters of the GA.

3.2.1 Setting for Exploration Ability of GA

To achieve a genetic search that keeps exploration ability, it is necessary to maintain the genetic disruption of the individuals in each generation[2), 5) 14)]. The selection of the schemes for genetic search and the setting of GA parameters are decided that the high genetic disruption is maintained.

The parameters of the (μ, λ)-linear ranking selection[2), 13)] are set as μ=64, λ=128 and η_{max}=1.5, and the uniform crossover[9), 11)] scheme is chosen. The experiment result of the relation to the energy convergence with the crossover and mutation occurrence probability is shown in **Fig. 2**. The low

[a)]The exploration and exploitation properties are generally used in the GA as the abstract concept of the global and local search abilities respectively[5)].

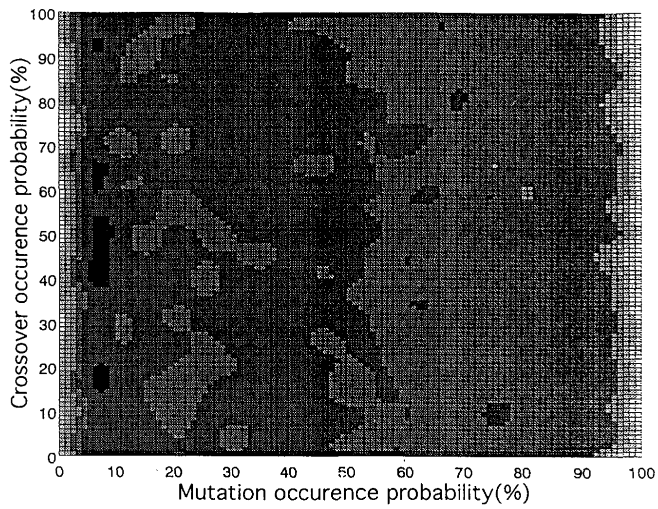

Fig. 2 Relation to energy convergence with crossover and mutation occurence probability

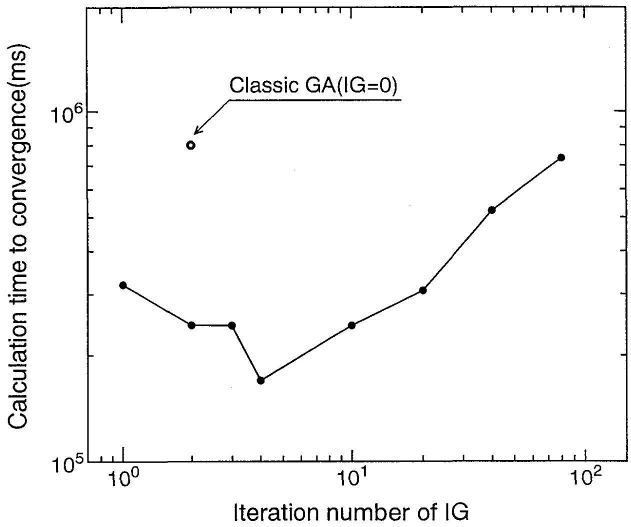

Fig. 3 Relation between iteration number of IG and calculation time to energy convergence

energy levels are shown darkly. Plotting of the curve in this figure is done based on the averaged values of 5 runs in each experiment. The value of p_c=0.5 and p_m=0.08 are set based on this result. Such examinations are made for all other parameters.

3.2.2 Setting for Exploitation Ability of GA

To give the GA local search ability, Intermediate Generation(IG) is developed. The IG is the virtual generation inserted between two true generations. The fitness of the individuals of current generation is improved, highly fit individuals are selected, crossovered and mutated to form the new individuals of potentially higher fitness by the IG, before using them as parents to define next generation. The IG has the similar features to the *building block hypothesis*. The local search is promoted further by adding several virtual generations in which the selection, the crossover and the mutation are performed in the same manner as the true generation. IG can improve the fitness of the individuals of the current generation. **Figure 3** shows the relation between the iteration number of IG and the calculation time to the energy convergence. An appropriate effect was achieved without extra calculation on IG=4, as shown in Fig. 3.

In addition, the Elitist strategy[5] is adopted. The elitist strategy guaranties that the best individual (elitist) of the current generation survives to the next generation. The stability of solution can be improved by the successive elitist.

4. Bi-phased Genetic Algorithm

4.1 Two Phases for Bi-phased Genetic Algorithm

The BIGA is constructed of two phases, which give the system both the abilities of local and global search simultaneously. The two phases are named the stable phase and the fluctuant phase. The former can improve the fitness of the individuals of the current generation by the IG. A characteristic of the stable phase is the stability of the solution by the IG and the successive elitist. The latter is named for the fluctuant property of the solution. The fluctuant phase is designed to emphasize the robust search ability of the GA. The solution of the fluctuant phase is allowed to be instable to some degree in order to extend the search space.

The purpose of the BIGA is to realize the better optimization by combining the robustness of the fluctuant phase with the exactness of the stable phase. So, the BIGA includes two set of parameters to realize the above conception. **Table 1** shows the two sets of parameters for the BIGA. The parameters of two phases

Table 1 Two sets of parameters for Bi-phased Genetic Algorithm

Para. / Phase	λ	μ	η_{max}	p_c	p_m	Elitist Strategy adopted?	IG Strategy adopted?
Stable	128	64	1.5	0.5	0.08	yes	yes
Fluctuant	128	64	1.5	0.5	0.08	no	no

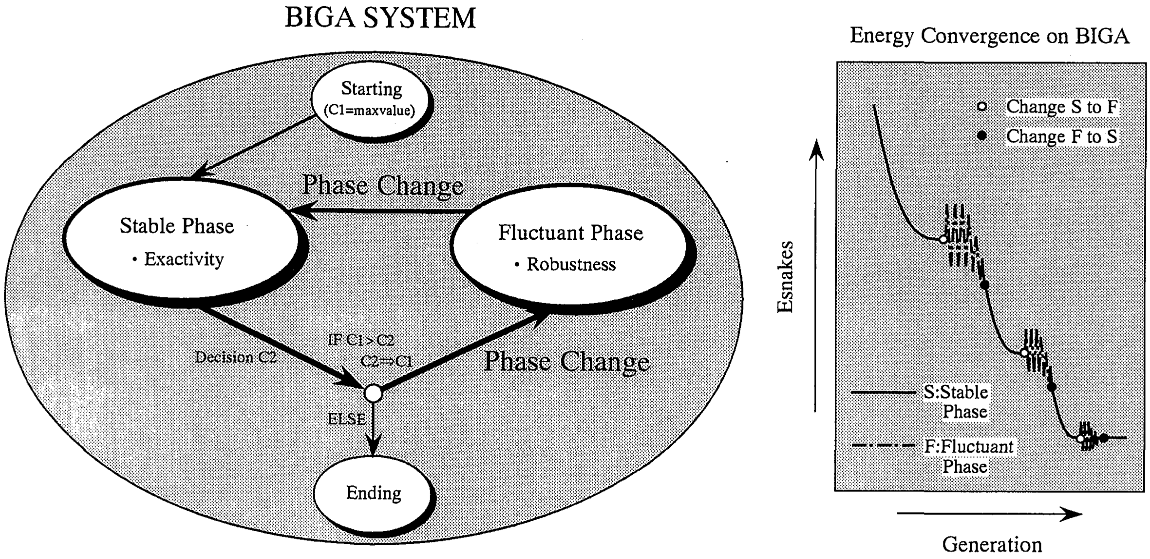

Fig. 4 Schematic diagram of the BIGA system for contour extraction

are different at the points where the elitist and the IG strategies are adopted or not. It is important to make the fluctuant phase keep the apposite search direction toward a suitable solution and the stable phase process without extra time. The decisions of the parameters are made empirically by the preliminary experiments.

4.2 Construction of the BIGA System

The BIGA system for contour extraction is originally constructed as follows:

Step 1. Initialize the system with the parameters of the stable phase(C1=maxvalue).

Step 2. Perform the process of the stable phase until the energy function converges at a certain level.

Step 3. Decide the candidate points(C2) of the active contour model based on the result of **Step 2**.

Step 4. Compare C1 with C2,
if C1 is larger than C2
then replace C1 with C2, and go to **Step 5**,
else go to **Step 7**.

Step 5. Change the phase of the system from the stable to the fluctuant.

Step 6. Go to **Step 2** after several generations at the fluctuant phase.

Step 7. Decide C1 as the final solution and finish the procedure.

Figure 4 shows the schematic diagram of the above algorithm. Once the curve of the total energy has settled at a certain level at the stable phase, the phase change occurs and the fluctuant phase starts. Escaping a miss-solution and progressing to a new solution are done at the fluctuant phase. The final solution is confirmed at the last stable phase.

5. Experiments

Experimental evaluation of the proposed algorithm was carried out on three points. The first was the calculational cost and the stability of the BIGA (stable phase, only) compared to the other algorithms. The second was the initial contour setting, and the last was the searching ability for the better solution in a noisy image.

The number of Snakes points on the curve, n was set to be 20, and α, β and γ, the weight coefficients in Eq. 1, were all set to 1.0. All other conditions were also the same.

5.1 Calculational Cost and Stability

The present method was compared to the other methods mentioned in subsection 2.2, with emphasis on the calculational cost and the stability of the solution for Snakes. The object image for the comparison of the methods is shown in **Fig. 5(a)**, where the initial contour curve for Snakes is set. The result images of convergence are shown in **Fig. 5(b)-(f)**. The decrease of the total energy of Snakes with time is shown in **Fig. 6**.

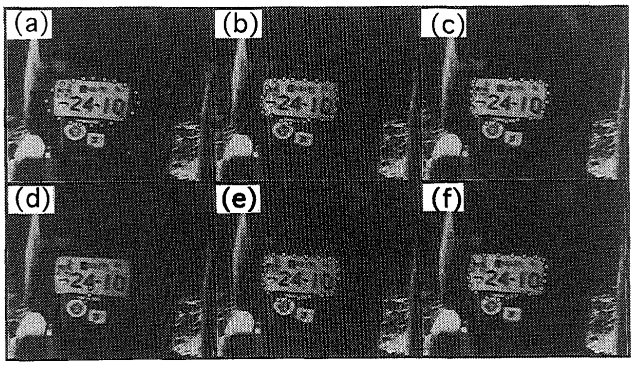

Fig. 5 Convergence results of active contours in stability test: (a) initial contour, (b) variational calculus, (c) open loop DP, (d) greedy method, (e) closed loop DP and (f) BIGA

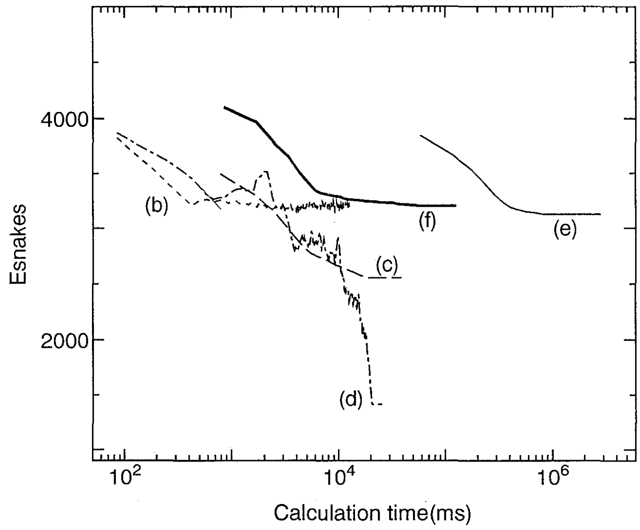

Fig. 6 Energy convergence of active contours in stability test

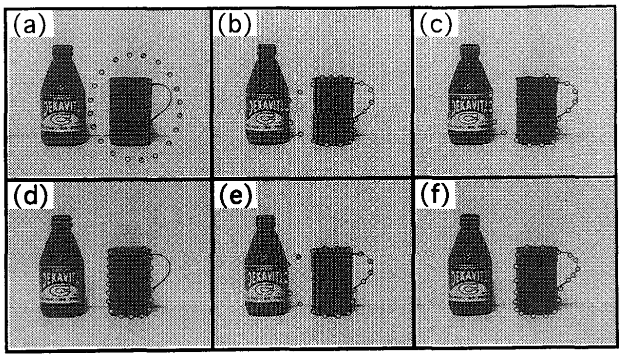

Fig. 7 Convergence results of active contours in initial contour setting test: (a) initial contour, (b) variational calculus, (c) open loop DP, (d) greedy method, (e) closed loop DP and (f) BIGA

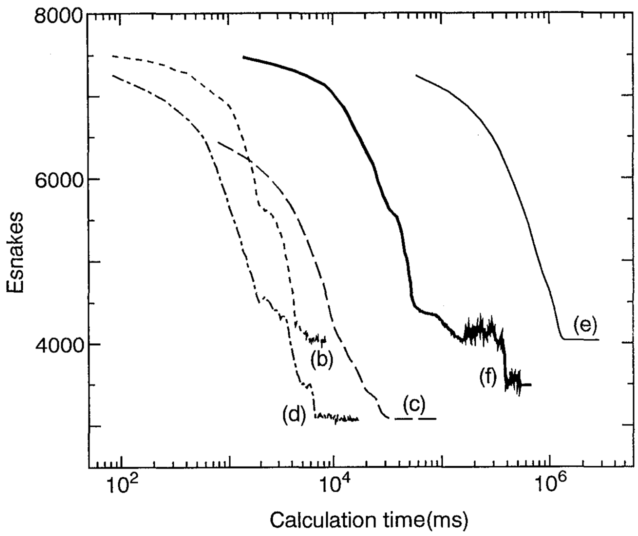

Fig. 8 Energy convergence of active contours in initial contour setting test

The processing speed becomes faster in the order, the variational principle, the greedy method, the open loop DP and others, as seen in these results. The curve of the greedy method converged to one point finally under this experimental condition because of its substantial property. The calculation costs of the closed loop DP and the BIGA are rather expensive, but their solutions are more stable than the other methods'.

5.2 Initial Contour Setting

The object image for the experiment is shown in **Fig. 7(a)**, where the initial contour curve is set at the midpoint between two objects, the bottle and the cup, in the image. The results of convergence are shown in **Fig. 7(b)-(f)**. The decrease of the energy of the spline curve with time is shown in **Fig. 8**.

The following facts are seen from these figures:

The processing speed of the greedy method is fastest. Some points of the contour curves had been drawn toward the neighboring object, the image of the bottle, the convergence finished at this state in the variational method, and the dynamic programming methods of the open loop model and closed loop model. This means that they fell into an undesirable local minimum and could not escape it. The convergence by the BIGA is proper although it takes rather time for the processing.

5.3 Searching Ability in Noisy Image

The performance of the system by noise was investigated by adding some amounts of noise to the image, and the convergence results are compared. A noisy image altered by adding salt-and-pepper noise of 20 percent noisy area ratio is shown in **Fig. 9(a)**. The

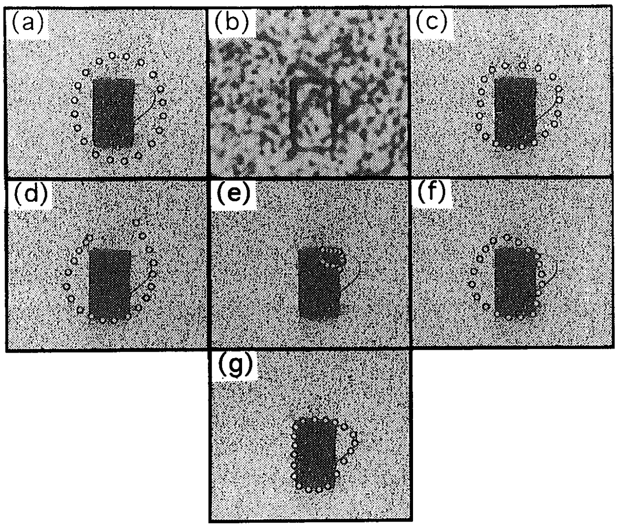

Fig. 9 Convergence results of active contours in robustness test: (a) initial contour, (b) external energy of (a), (c) variational calculus, (d) open loop DP, (e) greedy method, (f) closed loop DP and (g) BIGA

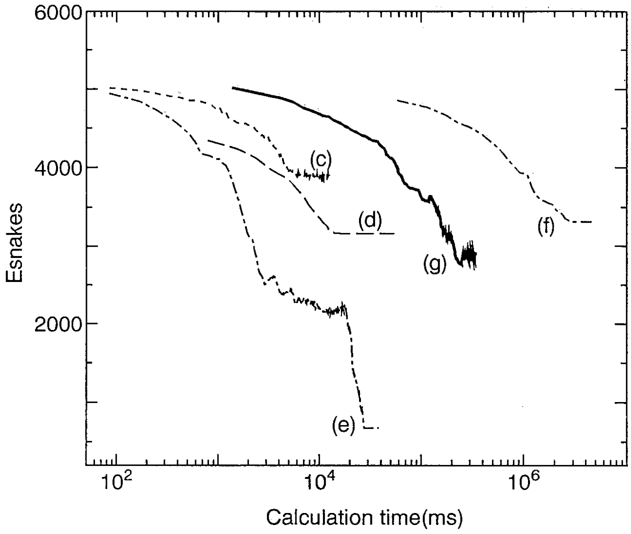

Fig. 10 Energy convergence of active contours in robustness test

image in **Fig. 9(b)** shows the external energy of Fig. 9(a). The processed results of the previous methods and the BIGA on the noisy image are shown in **Fig. 9(c)-(g)**. The decrease of the total energy of Snakes with time is shown in **Fig. 10**.

All of the results except by the BIGA were converged into false contours. Only the result of the BIGA was less influenced by the noise. As shown in Fig. 10, once the solution of the BIGA fell into the "holes" of the noise, it could escape them by the robust feature of the fluctuant phase. Such an effect was repeated several times, and finally, the BIGA succeeded in finding the true contour.

6. Conclusion

An active contour model was applied for extracting unlawful invasion object to construct a machine vision monitoring system. A minimization method for the active contour model using the genetic algorithm was proposed. The parameters of the GA were examined for the proper convergence of the energy function of the active contour model, and the suitable set of the GA parameters was obtained. To overcome the problems of the classic GA, the Bi-phased Genetic Algorithm was proposed to control the exploration and exploitation properties dynamically. The BIGA is constructed of two phases, each one having different features, and so it is possible to give the system both the abilities of local and global search simultaneously.

The processing results by the Bi-phased Genetic Algorithm were compared with those by the previous proposed methods, and the advantages of the proposed algorithm were proven by several experiments. It was confirmed by experiments that the BIGA has three key advantages for contour extraction:

(1) inexpensive calculation cost

(2) less governed by the initial contour setting

(3) robust to noise

The BIGA system can extract the contour of the object exactly and robustly.

References

1) Amini, A.A., Weymouth, T.E. and Jain, R.C., "Using dynamic programming for solving variational problems in vision", IEEE Trans. Pattern Anal. & Mach. Intell., vol. PAMI-12, no. 9, pp. 855-867, Sep. 1990.

2) Bäck, T. and Hoffmeister, F., "Extended selection mechanisms in genetic algorithms", Proc. 4th. Int. Conf. Genetic Algorithms, pp. 92-99, 1991.

3) Bhuyan, J.N., Raghavan, V.V. and Elayavalli, V.K., "Genetic algorithms for clustering with on ordered representation", Proc. 4th. Int. Conf. Genetic Algorithms, pp. 408-415, 1991.

4) Brown, D.E., Huntley, C.L. and Spillane A.R., "A parallel genetic heuristic for the quadratic assignment problem", Proc. 3rd. Int. Conf. Genetic Algorithms, pp. 406-415, 1989.

5) Goldberg, D.E., Genetic Algorithms in Search, Optimization and Machine Learning, Addison Wesley, 1989.

6) Inoue, K., Asano, K. and Seo, W., "Active contour extraction by genetic algorithm", Proc. Asia Conf. Comput. Vision, pp. 534-537, Osaka, 1993.

7) Kass, M., Witkin, A. and Terzopoulos, D., "Snakes: Active contour model", Int. J. Comput.Vision, pp. 321-331, 1988.

8) Mühlenbein, H., Schomisch, M. and Born, J., "The parallel genetic algorithm as function optimizer", Proc. 4th. Int. Conf. Genetic Algorithms, pp. 271-278, 1991.

9) Spears, W. and De Jong, K.A., "On the virtues of parameterized uniform crossover", Proc. 4th. Int. Conf. Genetic Algorithms, pp. 230-236, 1991.

10) Staib, L.H. and Duncan, J.S., "Boundary finding with parametrically deformable models", IEEE Trans. Pattern Anal. & Mach. Intell., vol. PAMI-14, no. 11, pp. 1061-1075, Nov. 1992.

11) Syswerda, G., "Uniform crossover in genetic algorithms", Proc. 3rd. Int. Conf. Genetic Algorithms, pp. 2-9, 1989.

12) Ueda, N., Mase, K. and Suenaga, Y., "A contour tracking method using elastic contour model and energy minimization approach", Trans. IEICE, vol. J75-D-II, no. 1, pp. 111-120, Jan. 1992.

13) Whitely, D., "The genitor algorithm and selection pressure: Why rank-based allocation of reproductive trials is best", Proc. 3rd. Int. Conf. Genetic Algorithms, pp. 116-121, 1989.

14) Whitely, D., Starkweather, T. and Fuquay, D., "Scheduling problems and traveling salesmen: The genetic edge recombination operator", Proc. 3rd. Int. Conf. Genetic Algorithms, pp. 133-140, 1989.

15) Williams, D.J. and Shah, M., "A fast algorithm for active contours and curvature estimation", Comput. Vision, Graphics, Image Processing., vol. 55, no. 1, pp. 14-26, Jan. 1992.