Application of Genetic Algorithm to Active Contour Model†

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Abstract

An active contour model called Snakes was proposed to extract a border line of an object in an image[1]. This method results in the minimization problem of the energy, which is defined on the contour curve. The authors obtained an excellent solution for this problem by applying a Genetic Algorithm(Define GA)[2] which simulates the principle of a living thing's selection and evolution. This application is further implemented in the transputer parallel processing system to improve the processing speed.

In this report, the method to apply GA to Snakes is described. The consideration is made on the parameters of GA to tune up its dynamic contour extraction ability. The comparison of the processing result by GA against those bythe various previously proposed methods is also described, and the advantage of GA is shown. This application of GA is installed in the parallel processing system composed of the transputers.

KEY WORDS: (Genetic Algorithm)(Active Contour Model)(Parallel Processing System)(Transputer)

1. Introduction

It is necessary to acquire the exact information on objects in the scene image in the automatic unlawful invader monitoring system. The outline configuration of the object is one of the most important features by which its attribute can be specified. An active contour model called "Snakes" was proposed to extract the outline of the object in the image. The "Energy" is defined on the closed curve around the object. To get the solution of this model and to extract the object configuration results in the minimization problem of this energy. Several methods, such as calculus of variations, dynamic programming and so called "Greedy", have been proposed to get a solution for this problem. All of them have disadvantages; for example, their processing time is too long, or they easily lead to a missolution depending on the parameter setting.

The authors obtained an excellent solution to this problem by applying Genetic Algorithm. The processed result by GA was compared with those by the previously proposed methods. This application was further implemented in the transputer parallel processing system to improve the processing speed.

2. Active Contour Model and Dynamic Outline Extraction

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, the curve converges to the contour of the object at the minimum point of the energy. The energy defined on the curve includes the internal spline energy, which depends on the shape and the size of the curve itself, and the external spline energy, which depends on the "image-potential" of the object.

The equation to define this energy is as follows:

$$\left.\begin{aligned} E_{snake}(v(s)) &= \int_0^1 \left[E_{in}(v(s)) + \gamma E_{ext}(v(s))\right] ds \\ E_{in}(v(s)) &= \alpha|v_s(s)|^2 + \beta|v_{ss}(s)|^2/2 \\ E_{ext}(v(s)) &= -\left[G_\sigma(v(s)) * \nabla^2 I(v(s))\right]^2 \\ G_\sigma(v(s)) &= \exp\left[-|v(s)|^2/2\pi\sigma^2\right] \end{aligned}\right\} \quad (1)$$

where E_{snake}, E_{in}, E_{ext} are the total, the internal and the external energy of the spline curve respectively. $v(s)$ 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 1. $v_s(s)$ and $v_{ss}(s)$ are the 1st and the 2nd

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differentiations with s. $I(s)$ is the intensity of the image at the point $(x(s),y(s))$. The constants α , β , γ are the coefficients of the weights for each term, and σ is the standard deviation of the Gaussian function $G_{\sigma}(v(s))$. The symbol * denotes the convolution.

3. Application of Genetic Algorithm (GA)

3.1 Basic concept of genetic algorithm

Genetic Algorithm(GA) is the algorithm which simulates a living thing's selection and evolution behavior, and it has recently received attention as a new method for optimization of the combination problem. In GA, the "Fitness" of a certain system to the "Environment" is defined on various combinations of its elements, which are called "Genes" metaphorically. The "Selection" is carried out on the basis of the fitness of the combinations of the genes. The combinations correspond to "Chromosomes", whose sets are formed at a certain generation so that a chromosome of higher fitness may be passed to the next generation with higher probability, and vice versa. After selection, the next generation begins, and the operations of "Crossover" and "Mutation" are given. These procedures are repeated until a combination of the approximately highest fitness is obtained. If we define beforehand the fitness so as to get the optimum solution, we can solve the optimization problem in terms of probabilities.

3.2 Application to active contour model

GA is the method used to decide the next step for each point on the active contour curve of a digital image. That is, every time a new active contour curve is formed, the calculation of GA for several generations is carried out, and the optimum direction for each point is decided. According to this decision, the deformation then proceeds and the next new curve is formed. The contour, or 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 any of 8-neighbors of the present position (here, the square pixel is assumed in the digital image), many combinations will generate for all points (n points). N sets are taken from these combinations arbitrarily at first. The example for n=N=20 is shown in **Fig.1**, where each set is expressed as the figure rows of the Freeman Chain Code. We consider each row an individual that has only one array of the genes (that is, only one chromosome), and perform the following operations between the individuals.

Selection :

Each individual is selected according to the selection probability P_i of Eq.(2)

$$P_s = f_i \Big/ \sum_{i=1}^{N} f_i \qquad (2)$$

where f_i is the fitness of the i-th individual obtained from Eq.(3).

$$f_i = 1-(E_i - E_{\min})/(E_{\max} - E_{\min}) \qquad (3)$$

where E_i is the energy of the spline curve, E_{snake}, calculated by Eq.(1), for the i-th individual. $E_{\max}$ and $E_{\min}$ are $Max(E_i)$ and $Min(E_i)$ respectively. The number of the set N is adjusted to be kept constant in the operation of selection.

Crossover :

The exchange of genes, parts of the chromosome, is performed between the i-th and the j-th individuals with certain occurrence probability.

Mutation :

The genes of the chromosome in a certain individual mutates with certain probability.

One generation finishes after the operations of selection, crossover and mutation. A new generation then begins, and the same operations are repeated. The

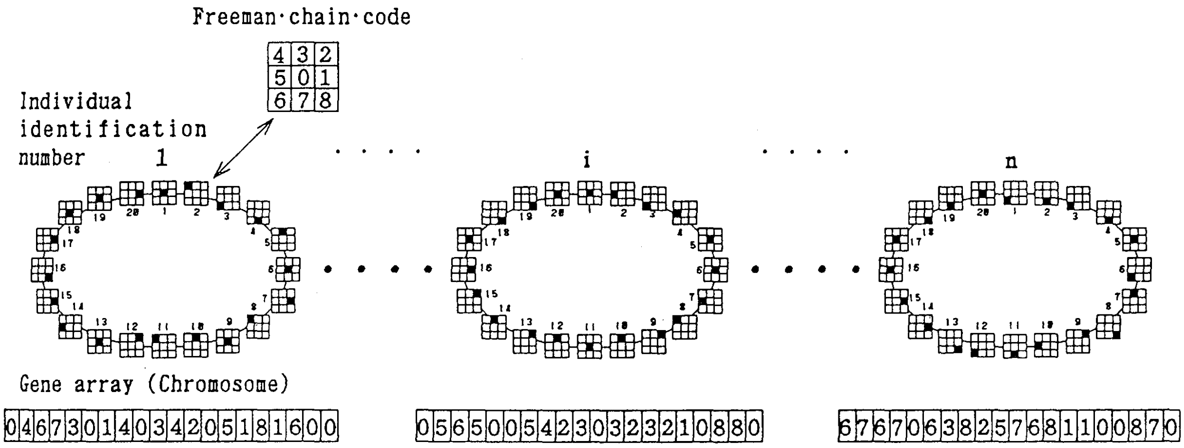

Fig. 1 Active contour model expressed by GA.

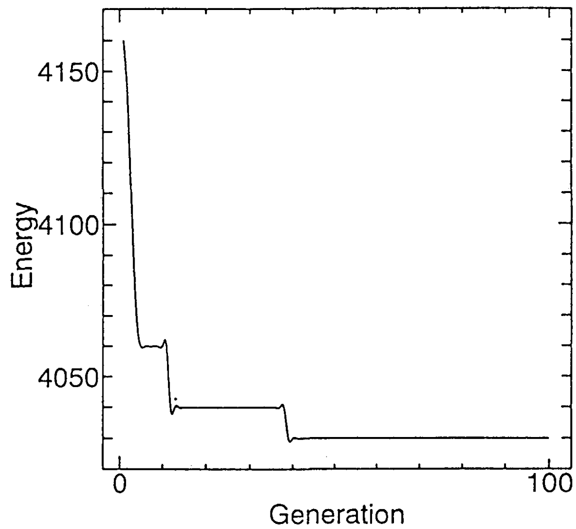

Fig. 2 Decrease of spline energy E_{snake} with time during 100 generations.

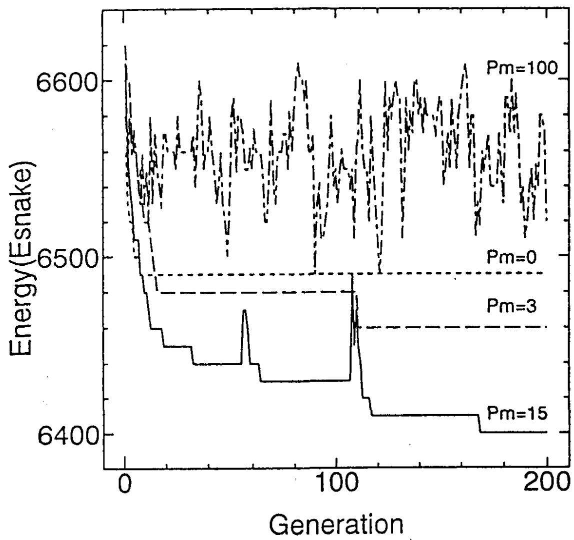

Fig. 4 Effect of mutation occurrence probability.

decrease of the total spline energy during 100 generations of our problem is shown in **Fig. 2**. A new curve is formed after 100 generations. The total spline energy decreases every time a new curve generates, and the curve converges around the target object in the image at last.

3.3 Examination of parameters in GA

Parameters such as the number of the individuals, the number of generations, and the occurrence probability for crossover and mutation should be determined according to the nature of the problem to be applied empirically. These parameters were examined for the present problem by numeric calculation experiments. The results are shown. **Figure 3** shows the effect of the crossover occurrence probability on the energy convergence. The effect of the mutation occurrence probability is shown in **Fig. 4**. It is understood from these figures that the proper

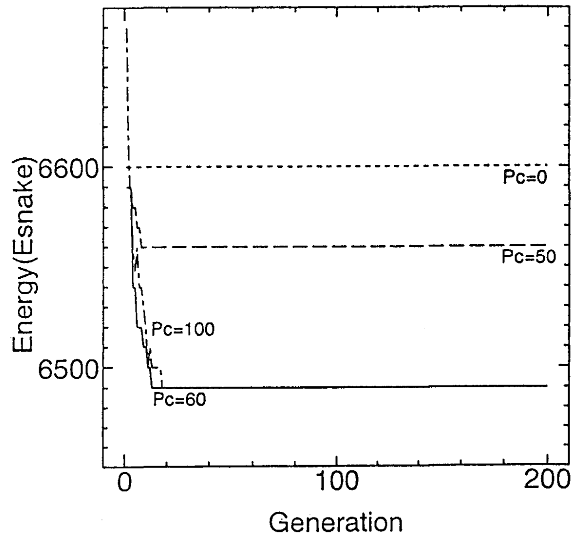

Fig. 3 Effect of crossover occurrence probability.

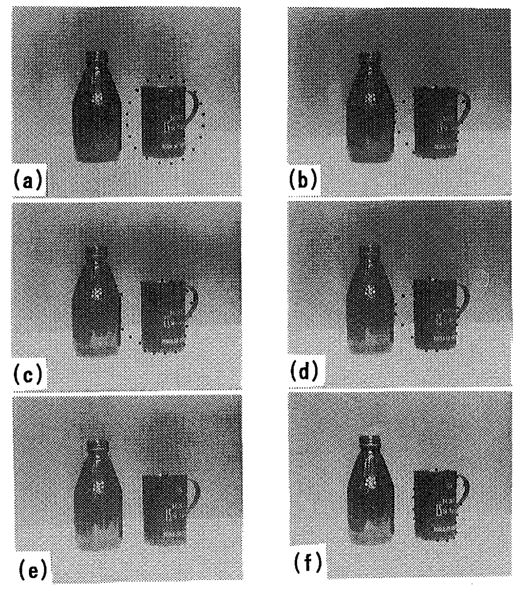

Fig. 5 Convergence results of active contours.

convergence is not realized without setting these parameters suitably. The examinations were made on the other parameters.

4. Comparison of present method with others

The present method was compared with other methods previously proposed as a solution for Snakes. The object image for comparing the methods is shown in **Fig. 5**(a), where the initial contour curve is set to pass between two objects, the bottle and the cup, in the image. The number of the points on the curve n was set at 20, and α, β, γ, the weight coefficients in Eq.(1), were all set to 1.0. All other conditions were the same. The spline curve convergence experiment was done with several different methods after the Sobel & Gaussian Filter preprocessing. The results of convergence are shown in Fig. 5(b) ~ (f). The decrease of the energy of the spline

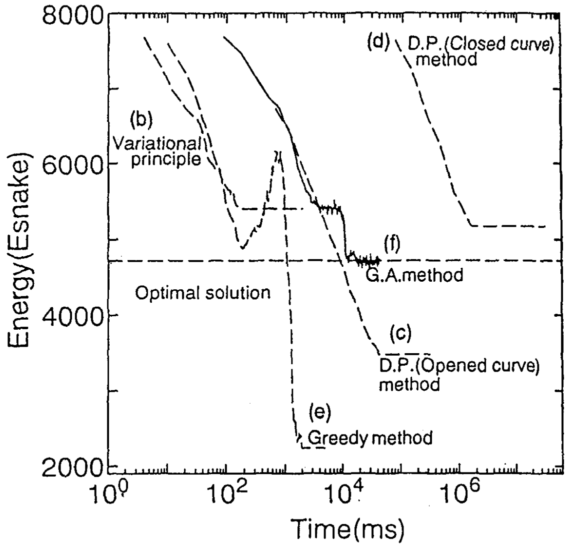

Fig. 6 Spline energy convergence in various methods.

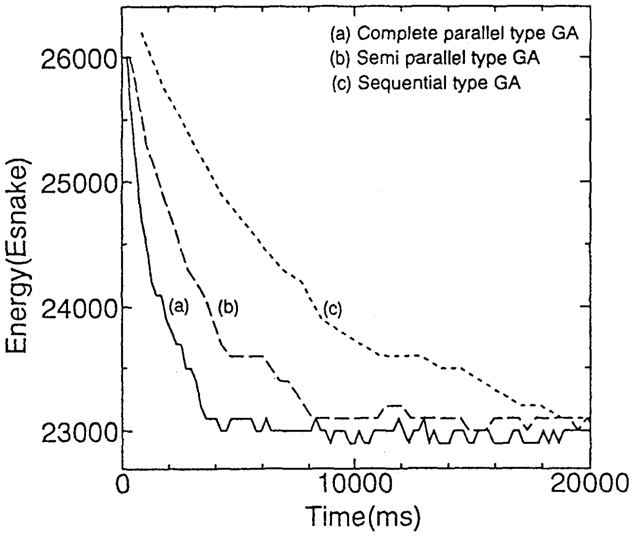

Fig. 8 Comparison of parallel processing algorithms in spline energy convergence.

curve, E_{snake}, with time is shown in **Fig. 6**. The following facts are seen from these figures: The processing speed of the Greedy method[3] is quickest, but the curve finally converged to one point under these experimental conditions because of the algorithm of this method. Some points of the contour curves had been drawn toward the neighboring object, the image of the bottle, and the convergence finished at this state in the variational method[1] and the dynamic programming methods of open loop model[4] and closed loop model[5]. That is, they fell into local minimum and could not escape it. The convergence by GA is proper although it takes substaintial time for processing.

5. Parallel Processing by Transputer System

The parallel processing for the outline extraction of

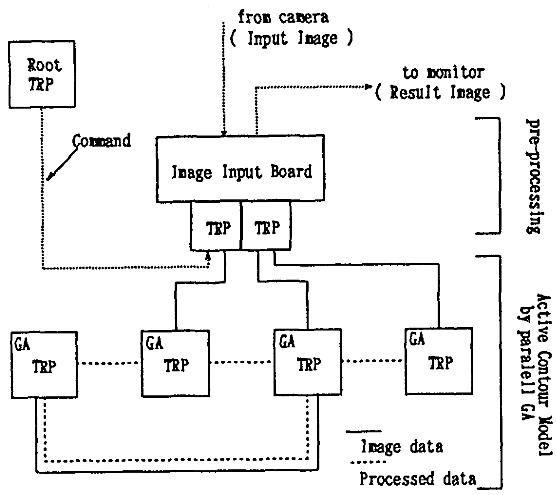

Fig.7 Parallel processing system by transputers.

the object by GA is examined by the transputer system. The transputer has four links which are connected to each other to form the network and perform the parallel processing[6]. The system shown in **Fig.7** was constructed by using the transputers and the image input board.

The effect of the parallel processing was tested on the following two types:

Type 1 : All individuals in a certain generation are divided into several blocks (in this present case, four blocks). Each block is assigned to each transputer,where only E_{snake} in Eq(1) is calculated. The calculated data of all transputers are collected to one specified transputer, where the gene operations of selection, crossover and mutation are performed based on the received data. One generation finishes after the operations of genes; then a new generation begins, and the same processing starts again for a new set of individuals. A new contour curve is formed after some generations. The same processing is repeated until convergence. In this type, the gene operations are performed for all the individuals in the same pool, so these parts of processing can not be done in parallel.

Type 2 : Not only the calculation of E_{snake}, but also the gene operations are performed in each transputer. The calculations are repeated generation after generation, and then the results are transmitted to one specified transputer after several generations. A new contour curve is formed as the result of the comparison with the data received from each transputer. In this type, the operations of the genes are done only for the individuals belonging to the same block at each transputer. That is, the pool of the genes is locally limited although approximately perfect parallel processing is possible. The energy convergence of the contour curve with time was compared with the above two types of parallel processing. The object image is the same as Fig.5(a). The result is shown in **Fig. 8**. The result by single processor is also shown in Fig. 8. Naturally, the processing speed of Type 2 is about two times faster than that of Type 1. However, the inconvenience due to a small pool of the genes in Type 2 does not occur, though it was somewhat anticipated before the experiment.

6. Conclusion

This report is summarized as follows:

(1) Genetic Algorithm(GA) is applied to the active contour model. An excellent result can be obtained if the parameters of GA are set properly.

(2) It is much harder for the method by GA to fall into the local minimum than for previously proposed other methods in active contouring.

(3) The parallel processing system for GA is developed, and its performance is also examined.

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