5—1 Automatic Generalization of Image Transformation Processes Using a Genetic Algorithm

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Abstract: A method is proposed to generalize the image transformation from an image to another one according to a pair of example images. When an original image and its target image are given, the unknown image transformation from the original image to the target one is automatically approximated by a sequence of several known image transformation filters by the method. The target image is assumed to be generated manually by using a drawing software. In this method, the order of image transformation filters is regarded as the chromosome of a virtual living thing and is evolved according to Genetic Algorithm. This method can be applied to automatic construction of expert systems for image processing.

1 Introduction

In primary image processing, original images should often be preprocessed by filtering such as smoothing, edge enhancement, noise reduction, binarization and so on to make adequate images to following processes. In many cases, however, we do not know what kinds of image filters should be operated in how order. An expert who knows well about image processing, therefore, has to transform the original image to get the adequate image through trials and errors. In order to assist such an operator, several image processing expert systems have been proposed[1][2]. In such expert systems, we can construct image transformation processes interactively by using GUI. Since this is a laborious job, several expert systems can automatically generate the image transformation process from an original image to its ideally processed image according to given several examples. Using such expert systems, we can construct the image transformation if we prepare several sample target images. In such conventional expert systems, however, image transformations which can be generated are generally restricted since the total number of transformations becomes vast when we use many image filters. We propose, therefore, an effective automatic construction method for image transformation. This method is based upon a *Genetic Algorithm;GA*[3][4][5]. In our GA, a sequence of image transformation filters such as smoothing, edge enhancement and so on is regarded as the chromosome of a virtual living thing. Each individual is evaluated by his fitness value which is calculated from difference between a given target image and the image processed by the image filter sequence determined by its chromosome. The initial population of such individuals is randomly generated and is evolved according to GA operations, i.e. *selection*, *crossover* and *mutation*. Through generation iterations, the adequate image transformation is generated.

2 Genetic Algorithm

In this section, Genetic Algorithm is briefly surveyed. *Genetic Algorithm;GA* is one of optimizing / searching algorithms which are categorized in *Evolutionary Algorithms;EAs*. EAs include *Evolution Strategy;ES*, *Evolutionary Programming;EP*, Genetic Algorithm;GA, *Genetic Programming; GP* and so on. Among these algorithms, GA is the most popular one and is used in various fields. In GA, a population of virtual living things which have chromosomes corresponding to solutions of a given optimizing problem is evolved according to *natural selection*. Each individual is evaluated by his *fitness* value. In the recombination process, inferior individuals are removed and superior ones make their children to keep the population size constant. When parents make their children, their chromosomes are cut and pasted to make chromosomes of their children. This operation is called *crossover*. Moreover, each gene of all individuals is randomly changed according to a very small occurrence probability named mutation ratio. These processes are executed repeatedly until individuals corresponding to good solutions appear. Figure 1 illustrates the basic flow of GA.

```
initialize_population;
calculate_fitness;
repeat
    recombination;
    crossover;
    mutation;
    calculate_fitness;
until good_solutions_are_obtained;
```

Figure 1 : The basic flow of GA

3 Automatic Generalization of Image Transformation

3.1 Principle

Figure 2 illustrates the principle of our method.

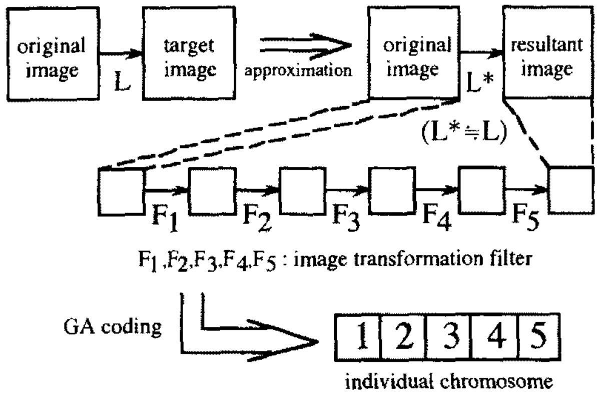

Figure 2 : The principle of the research.

As shown in Figure 2, an original image and its ideally processed image are assumed to be given. We call the ideally processed image *target image* in this research. We have to make a target image manually by using an interactive drawing software. The image transformation L from the original image to the target image is approximated by L^* which is a sequence of known image transformation filters. In Figure 2, L^* is composed of five filters F_1, F_2, F_3, F_4 and F_5. We can employ any image transformation filter if its input and output are images of a constant size. As examples of such image transformation filters, we know many kinds of filters such as smoothing, thresholding, edge enhancement filters and so on.

3.2 Definition of chromosome

We have to determine the sequence of image transformation filters so that it approximates adequately the image transformation from the original image to the target image. As determination of the image filter sequence can be regarded as an optimization problem to determine the order of filters, we can apply GA to this problem effectively.

In GA, chromosomes of individuals represent solutions of a given optimization problem. In our coding of GA, therefore, chromosome of an individual is encoded as a string which represents a sequence of filters. In the example shown in Figure 2, the string corresponding to the image filter sequence is '12345'.

For an image filter which requires one or more numerical parameters, we consider several cases with typical parameter sets and give them different identifiers. For instance, when there are two types in i-th image filter with parameter sets (8, 20) and (20, 64), respectively, we encode them by strings 'i1' and 'i2'.

3.3 Definition of fitness

Each individual is evaluated by the fitness value in GA as described in section 2. In the proposed method, fitness value f_i of i-th individual I_i is defined by using differences in pixel values between the target image $g(x, y)$ and the image $h(x, y)$ obtained by the image transformation denoted by I_i's chromosome. That is, f_i is calculated from

$$f_i = 1 - \frac{\sum_{x=1}^{W_x}\sum_{y=1}^{W_y} |g(x,y) - h(x,y)|}{range \bullet W_x \bullet W_y} \qquad (1)$$

where W_x and W_y are width and height of the image respectively, and *range* means the pixel value range and is 255 in this paper.

3.4 GA operators

3.4.1 Selection rule

We generate the initial population composed of several individuals who have randomly generated chromosomes, and we evolve them according to GA. In generation iteration, we employ the basic selection rule named the *roulette rule*. In the roulette rule, an individual whose fitness value is f_i is selected as a new individual of the next generation according to the probability

$$P \propto \frac{f_i}{\sum_{j=1}^{N} f_j} \qquad (2).$$

This rule realizes natural selection based on fitness values. We also employ the *elitist strategy* that always select the elitist of the current generation as a new individual. By this strategy, the maximum fitness value of the population increases monotonously during generation iteration.

3.4.2 Crossover

As the length of individual chromosome is not constant in this method, we cannot use conventional crossover operators. We employed a modified one-point crossover as illustrated in Figure 3.

In this crossover, two parental chromosomes P_1 and P_2 are divided into two parts at randomly selected crossover points respectively, and they are recombined to make offspring chromosomes O_1 and O_2 as shown in Figure 3. In this process, crossover points are set between image filter identifiers.

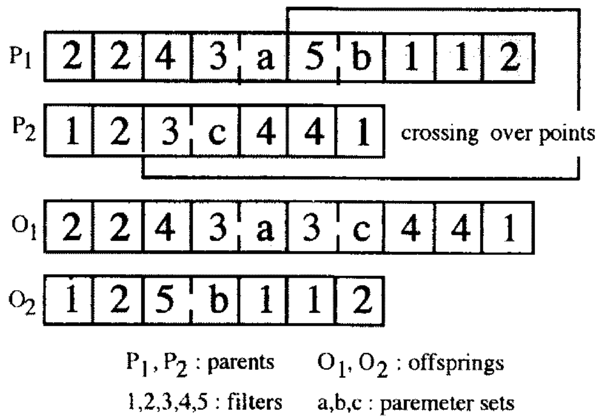

Figure 3 : Modified one-point crossover.

3.4.3 Mutation

After the new individuals have been determined as the new generation, mutation operation is carried out. In mutation, each gene of every individuals is randomly changed according to the occurrence probability named mutation ratio, which is 1[%] in this research. When mutation occurs at a certain gene, the image filter corresponding to this gene is exchanged by a randomly selected image filter.

4 Experiments

Figure 4 and Figure 5 illustrate an original gray-leveled image and its ideally processed image respectively. The ideally processed image was made manually and was regarded as the target image for the image transformation optimization. The following five kinds of filters F_1, F_2, F_3, F_4 and F_5 were used;

- F_1 : binarization filter,
- F_2 : minimum value filter,
- F_3 : maximum value filter,
- F_4 : reverse filter,
- F_5 : subtract filter (original image - processed image).

Figure 6 and Figure 7 illustrate the obtained image by the method and the filter sequence in this case respectively. We can see from these figures that automatic construction of image transformation has been achieved successfully by our method. As there are several isolated character regions in Figure 4, it is not so easy to extract the figure shown in Figure 5 only by filtering. It should be noted that the manual extraction process to make Figure 5 can be successfully approximated by a sequence of simple known image transformation filters by the proposed method. Since GA is a stochastic algorithm, the optimized filter sequence is not determined uniquely. The sequence shown in Figure 7 is one of adequate sequences.

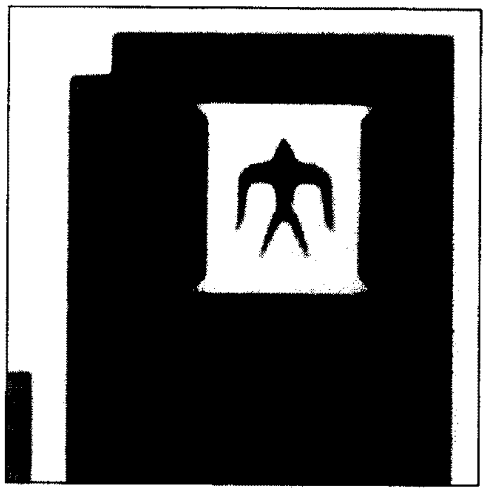

Figure 4 : An original image.

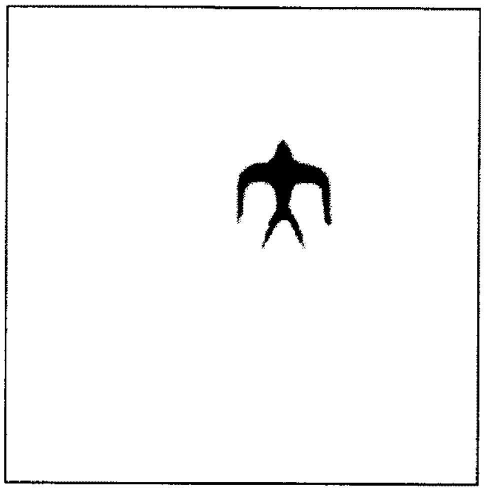

Figure 5 : Ideally processed image.

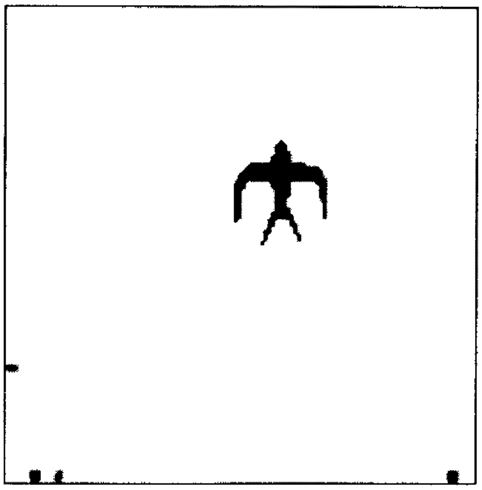

Figure 6 : Obtained image.

3 3 3 2 2 2 5 1 3 2 4

Figure 7 : Obtained filter sequence.

We show more several experimental results. Figure 8 is an original map image input by using an image scanner. The original map is one of the most typical 1/25,000 scaled maps in Japan. We generated the image shown in Figure 9 manually and used it as the target image of the original image shown in Figure 8. By the proposed method, the image transformation from Figure 8 to Figure 9 was approximated by the image filter sequence as illustrated in Figure 11. The image illustrated in Figure 10 is the obtained image by this image filter sequence. By using the filter sequence shown in Figure 11, the new map images illustrated in Figure 12 and Figure 14 were transformed into the images shown in Figure 13 and Figure 15, respectively. From these figures, we can see that the image transformation to extract Japanese Characters 'Kanji' from maps has been roughly generated by the method. Since extracted regions contain noisy figures which are not characters, we should use not only the proposed method but also conventional methods to extract characters precisely. However, the proposed method can be used as the preprocessing to find out candidate regions of characters.

In the above experiments, we did not take account of the length of image filter sequence. That is, the lengths of an optimized filter sequence is not necessarily short. Moreover, the obtained solution is not necessarily the best filter sequence but one of good solutions, and it may contain unnecessary parts or it should be shortened.

It is suggested that we can construct more complicated image transformations by adding many new image filters to our system. When we use a lot of image filters, however, we have to consider the increase of computation time since the total number of combinations of filters becomes vast in such a case. Moreover, we have to investigate the performance of the proposed method though many experiments in order to verify the generality of the method.

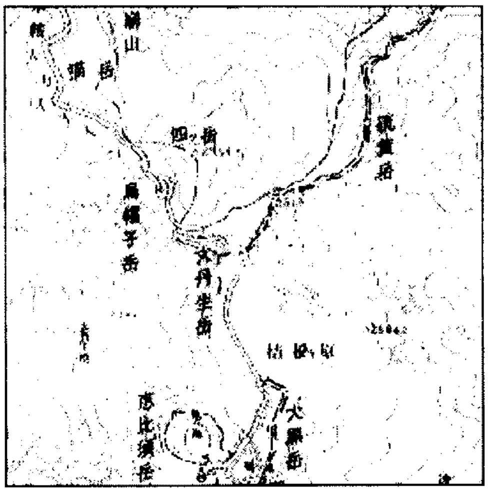

Figure 8 : An original map image.

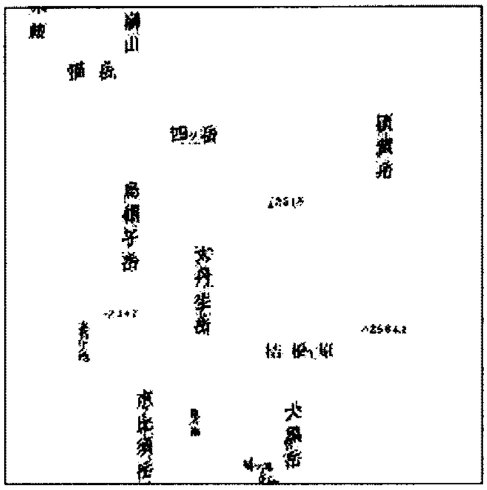

Figure 9 : The target image.

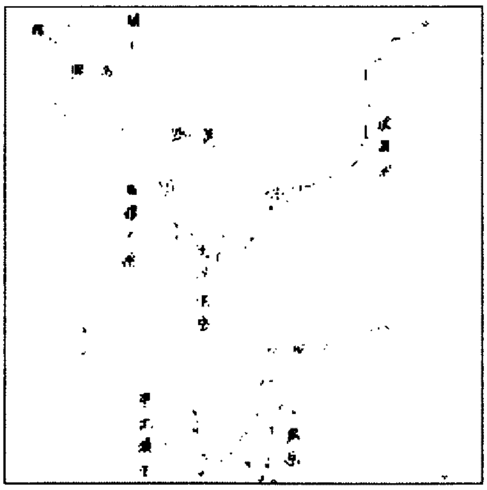

Figure 10 : Obtained image.

3 2 5 5 3 3 2 2 3 2 2 3 5 5 1

Figure 11 : Obtained image filter sequence.

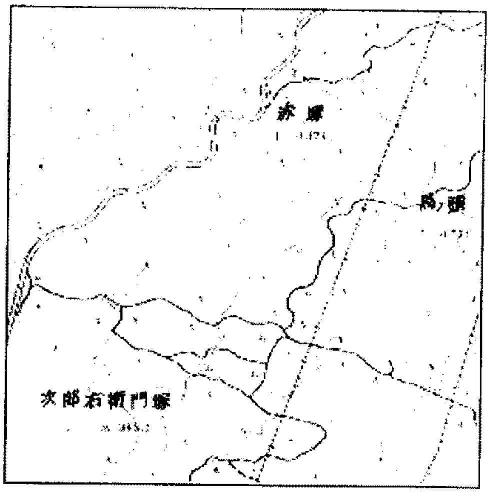

Figure 12 : New image No.1.

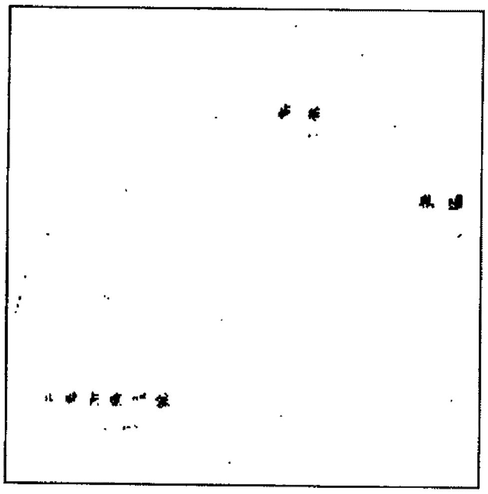

Figure 13 : Transformed image No.1.

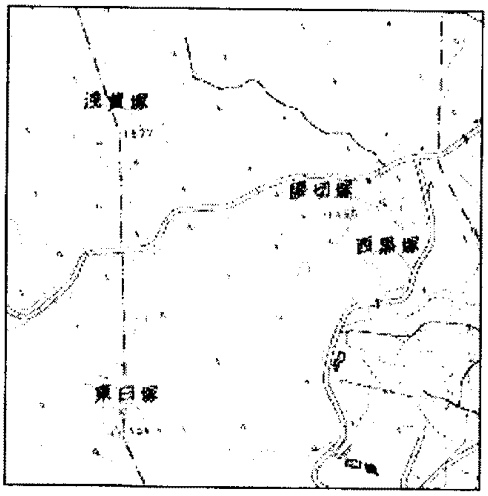

Figure 14 : New image No.2.

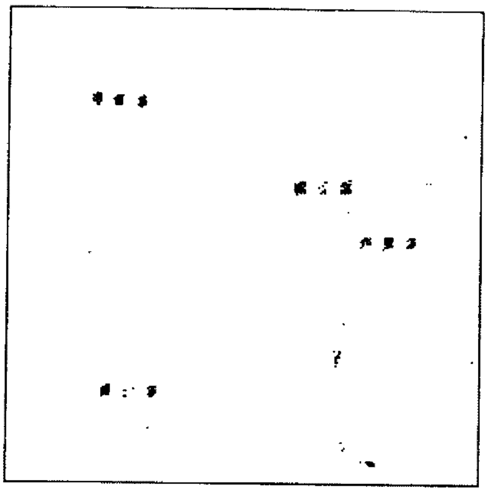

Figure 15 : Transformed image No.2.

5 Conclusions

A method to generalize the image transformation from an original image to its target image is proposed. This method is based on Genetic Algorithm, and the order of image transformation filters is optimized according to GA. By using the method, we can construct image transformation processes composed of known image filters only from a pair of example images. Experimental results show that the method can approximate successfully unknown image transformation by sequences of known image filters. We are planning to treat more complicated image transformation by adding new image filters.

References

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