IMAGE PROCESSING AND INTERACTIVE SELECTION WITH JAVA BASED ON GENETIC ALGORITHMS

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Abstract:
Knowledge acquisition systems for image enhancement procedures have been developed using Java. Based on genetic algorithms (GAs), the systems can optimize procedures for enhancing target components in the digital images of plants in fields. Using rough objective images given by users as a standard image for evaluating fitness, it can provide appropriate filtering operations and their parameters. To improve convergence, interactive selection, which selects a promising individual by human intention instead of the fitness function, has been introduced. Consequently, the combination of the fitness function and interactive selection has contributed to rapid convergence of the processing.

Keywords: GA, Image processing, Image enhancement, Interactive selection, Java, Knowledge acquisition

1. INTRODUCTION

The tide of studies on monitoring is changing with the growth of the Internet. Now, easy and immediate acquisition of large numbers of digital color images of the daily growth of plants in remote fields has been made possible via the Internet with simple video cameras, which are placed in the fields and connected to the Internet. From such images, we can expect that detailed information concerning the shape, growth rate and leaf colors of plants will be obtained. Vast quantities of image data, however, increase the time spent extracting such information from the data. This is because the extraction procedure needs human aid - empirical knowledge of image processing and the features of target objects. Image analysis, segmenting images of plants and deriving outlines or areas of the objects from the images, commonly invoke procedures based not only on routine, but also on trial and error performed by hand.

Automatic image processing systems, such as expert systems, have been investigated in various areas of engineering. Nazif and Levine (1984), Mckeown *et al.* (1985) have studied rule-based expert systems for an automatic segmentation of monochrome images, linked to a knowledge base on the target objects. These expert systems, however, have had common difficulty that they must implement vast networks of complex rules, and exercise empirical knowledge on image processing and the features of objects. To overcome such difficulty, automatic and easy optimization of procedures for image enhancement has been studied (Shibata *et al.*, 1993). Fortunately, we can easily use color image data and high performance PCs nowadays. Since color images have considerable information needed for enhancing targets in images, appropriate enhancement has the potential to simplify the rules used by expert systems.

In this study, we have emphasized the procedures for selecting filtering algorithms and for tuning their parameters to enhance target components in images. Genetic algorithms (GAs) are suitable for this purpose because the algorithms involve optimization and automation by trial and error. For instance, Fitzpatrick and Grefenstette (1988) have applied GAs for obtaining optimal image processing transformations mapping the original image into the target one. From the viewpoint of enhancing images of plants, we present application software based on GAs, not only for enhancing images, but also for acquiring knowledge on the enhancement operations.

2. METHODS

2.1 Image processing strategy

Many kinds of efficient filtering algorithms for image enhancement, such as noise elimination and edge enhancement, have been contrived (Gonzalez and

Table1 Filtering algorithms used as phenotypes

Manipulation	Algorithms	Sym-bols
Thresholding (hue)	Point processing	TH
Thresholding (brightness)	Point processing	TB
Smoothing	Median operator	SM
Edge enhancement	Sobel operator	EE
Contraction	4-neighbor fusion	CF
Expansion	4-neighbor fusion	EF
Reversion	Point processing	RV

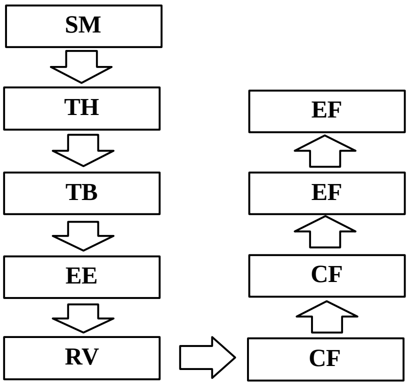


Fig.1 Flow chart of a typical procedure for enhancing targets components. Not all of the operations are applied to the enhancement.

Woods, 1993). Implementing all of them into our algorithms, however, is unrealistic because the increase in operations invokes a proportional increase in processing time. Based on our empirical knowledge of the enhancement of plant images, we have selected several filtering algorithms used commonly, and implemented in our algorithm as shown in Table 1. The thresholding and reversion algorithms are performed on a pixel focused of the image processed in serial order, and the others have spatial mask operators.

While Hasegawa *et al.* (1988) has described common procedures for edge enhancement of monochrome images, common procedures to enhance targets in color images are considered as shown in Fig.1. The procedures are explained as follows:

1) Area color of components in the images is averaged using smoothing (SM).
2) Target components are enhanced using thresholding on hue (TH) and, simultaneously, the image is entirely converted to a monochrome image.
3) Differentiation (EE) is used when target features outline components.
4) Binarization (TB) is performed for the entire monochrome image.
5) Reversion (RV) on binarized pixels is occasionally effective to enhance the components.
6) Fusion operations, expansion (EF) and contraction (CF), allow a reduction in noise, and occasionally, is performed repeatedly.

After this procedure is done, the image processed has been converted to a binarized image with target components defined. In our algorithm, we have adopted not the RGB color model, but the HIS model, because the latter is efficient for the segmentation of plants in fields (Kusano *et al.*, 1997). All operations are performed after each pixel value is converted from RGB to HIS. The smoothing algorithm is a median operator with a 3×3 mask of pixels, and it is applied only for the hue of the pixels. The thresholding has two different operators; one operates upon the hue and another upon the brightness of pixels. These operations substitute null for all bits of a pixel when the pixel value occurs within a range defined by minimum and maximum values. When the value is out of this range, they substitute unity for all bits of the pixel. For edge enhancement of components in images, a Sobel operator with a 3×3 mask of pixels is used. The operator applied to the brightness value substitutes null for the saturation of pixels to convert the images to monochrome ones. Fusion operators search the four neighboring pixels. The contraction replaces a given pixel with a black one if the neighbors contain more than one black pixel. The expansion, on the other hand, replaces the given pixel with a white one if the neighbors contain more than one white pixel.

Before the genetic operations are applied, an objective image to be compared with processed images for fitness evaluation must be provided as a binary drawing image. Target components in the image are represented with white pixels and the remainder are represented with black ones.

0 – 5	6 – 9	10 – 15	16 – 19	20 – 22	23 – 25
TH (minimum)	**TH (range)**	**TB (minimum)**	**TB (range)**	**On-off of TH**	**On-off of SM**

26 – 28	29 – 31	32 – 34	35 – 37	38 – 40	41 – 43
On-off of CF	**On-off of CF**	**On-off of EF**	**On-off of EF**	**On-off of EE**	**On-off of RV**

Fig.2 Locus of genes defined on a chromosome. Each gene consists of several binary strings and has different length depend on its information. A continuous value was binarized with 4 to 6 strings and “on-off” of filtering was encoded with 3 strings.

2.2 Genetic algorithm

Chromosomes of the current GA consist of 44 binary strings or genes. Phenotypes of the current algorithm, consisting of an on-off state of the operations mentioned above and parameters for the operations concerning thresholding levels, are assigned in the chromosome as shown in Fig.2. The hue and the brightness range from 0.0 to 1.0. Minimum thresholding levels are encoded with 6 bits of the length of the gene. Similarly, their thresholding range is encoded with 4 bits. The genotype of the on-off state for each operation is encoded with 3 bits; a decimal value in range 0 to 3 is defined as an “off” state of the operation and a value of more than 4 as “on”. This encoding is redundant, and allows sharp changes caused by one bit reversion to be avoided.

Figure 3 shows the procedure for our algorithm, combining GA with the image processing described. In the procedure, we have used conventional genetic operations called “simple GA” (Mitchell, 1996); crossover at the same points of two neighbor chromosomes, random mutation, and ranking depending on fitness evaluation and selection. The crossover occurs at the points of certain string length determined at random, and each string in a chromosome is mutated with a probability of 0.02 per gene. Originally, GAs were implemented as iterative, parallel processing procedure. This indicates that an increase in population is similar to an increase in generation number when searching for acceptable approximate solutions. From this viewpoint, the population size is fixed to 40 individuals in order to observe changes in fitness depending on generations. At the beginning, all chromosomes are initialized at random. Before evaluating fitness, each chromosome is interpreted as a sequence of filtering operations. Subsequently, a clone of the original image is processed dependent on the each sequence.

Evaluation and selection play important roles in GAs because they determine the GA’s performance of searching the space of problems. We, therefore, have implemented two different methods for selecting a promising individual in our algorithm. One is selection depending on a fitness function, called ‘automatic selection’ in this study. The function is defined by the rate of correspondence between a processed image and an objective one, given as a successfully processed one. In detail, equivalence of each pixel, located in the same coordinate of both images, is verified. This is represented by the following formula:

$$f = P_{fit} / \left(P_{fit} + P_{unfit} \right)$$

where P_{fit} is the number of pixels equivalent between images and P_{unfit} is the number in disagreement.

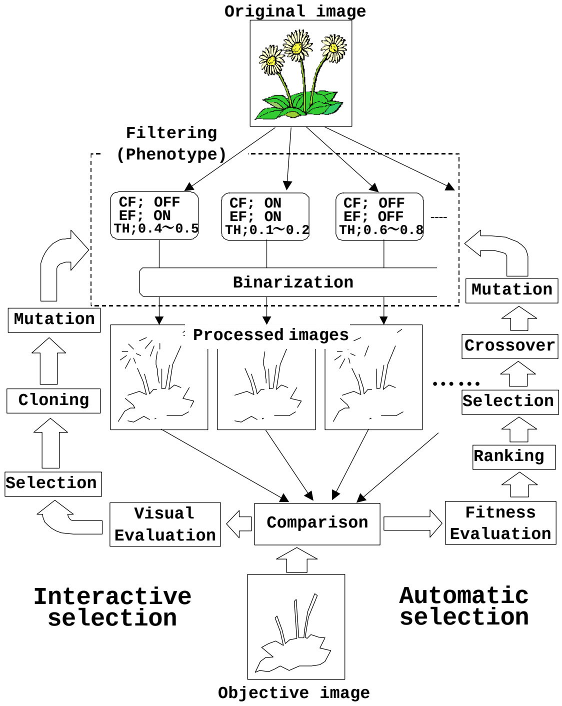


Fig. 3 Schematic of the knowledge acquisition system, combining GA and image enhancement operations.

Individuals are ranked according to their fitness. Then, individuals high in rank are selected until the initial population is obtained and the remainder are dumped. Another selection method depends on the visual acceptance of users, called ‘interactive selection’ in this study. Although the fitness function can search a vast space of problems, it cannot precisely replace the human ability to cognize visual images and to estimate potential. Introducing evaluation by users, instead of by a fitness function, has the advantage of applying rapid, heuristic cognition of the images in the current algorithm. In this operation, only one individual is selected as an original chromosome for the next generation and all the others are dumped. After cloning to the initial population size, the individuals are mutated with probability 0.1 per gene, and then, become the next generation. This operation corresponds to an artificial evolution, which Dawkins (1989) has proposed as a Biomorph by human intention. These two selection methods can be applied, both independently and jointly.

2.3 Programming

Application software implementing the GA described has been programmed using the Java language. Java has been used so that the software can remain platform-neutral; the software can work on various operating systems and in parallel via the Internet with distributed object architectures. The software has been made as a stand-alone application for accessing data files stored in local computers. Based on object-oriented programming, the software contains four classes: GA class, Process class, Filters class and MainFrame class. The GA class inherits Thread class and holds methods of genetic operations such as ranking, selection, crossover and mutation. The Process class inherits Object class, and holds methods for interpretation from genotypes to phenotypes, image processing control and fitness evaluation. The methods for control and evaluation work in the thread process of the GA class. The Filters class inherits Object class and holds the methods of spatial filtering described above. Instances of this class are created in the instance of the Process class. The MainFrame class inherits Frame class and holds GUI components, main menus and a viewer for presenting an original image and a standard one.

The software has various user interfaces for setting the conditions of the GA. Using a drawing interface to make objective images, users can easily select components in the image to be processed and binarize standard images. Condition interface allows users to change the initial conditions: population, length of chromosome, mutation frequency and generation on termination of the GA. Although initial phenotypes are determined at random in common genetic operations, we have implemented this interface to define the initial phenotypes by hand. Since the determination based on users' knowledge narrows down the searching space of solutions by the current algorithm, rapid acquisition of acceptable images might be expected. The Results of the genetic operations are presented as phenotypes by a phenotype presentation interface, which interprets the genotype of a champion individual. Using this interface, knowledge of enhancement technique to produce acceptable images can be obtained. An artificial selection interface is optional but in this study essential. It presents 20 images processed according to their genotypes. Based on their valuation, users can select the most acceptable image by hand, and use the genotype as the original one for the next generation.

In the current study, the software has been implemented on a PC with a Pentium Pro processor (180MHz) and Microsoft Windows NT version 4.0.

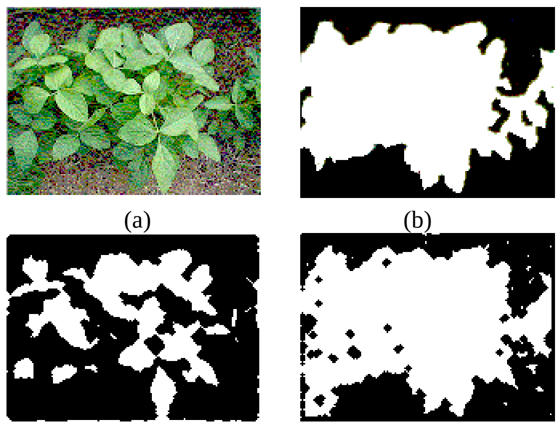
2.4 Specimens

The pictures used are in GIF format with 256 RGB colors and a size of 640×480 pixels. They had been taken with an off-line digital camera and stored in a PC. Their size was decreased to 160×120 pixels by a reduction in the resolution, in order to shorten the time for processing.

3. RESULTS AND DISCUSSIONS

3.1 Performance of automatic selection

An image of soybean plants, grown in our field, has been processed to check the algorithm using automatic selection. The standard image, Fig. 4(b), has been made as an objective image to enhance the leaf area of the plants on the original image, Fig. 4(a). The sequence of enhancement operations obtained first, the chromosome with the highest fitness in the first generation, provided an image far from the standard, as shown in Fig. 4(c). The sequence was as follows: TB ranging from 0.62 to 1.0, SM, RV and twice iterations of both EF and CF. Subsequently, in the 8th generation, the nearest image to the standard one, Fig. 4(d), is shown. The GA has automatically



(c) (d)

Fig. 4 Results of processing an image of soybean plants in the field: (a) an original image; (b) an objective image given; (c) an image processed by the procedure obtained at the first generation; (d) an image processed by the procedure obtained at the 8th generation.

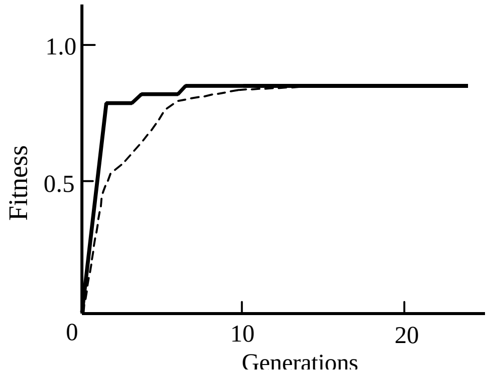


Fig. 5 Development of the fitness of an individual, depending on generation. The solid line is the highest fitness and the broken line the average fitness in each generation.

presented an acceptable sequence of image enhancements in the following: TH ranging from 0.21 to 0.41, TB from 0.05 to 1.0, RV and twice iterations of both EF and CF. Figure 5 shows that development of the average fitness has converged on the highest value by 15th generation. This shows that the group has lost its variety of genotypes and would not produce more fit genotypes. To provide an image more acceptable than this, elimination method based on knowledge of the object, for example, regularity of shape and area, would be necessary. The knowledge obtained by the current algorithm, however, will help to make the elimination process efficient.

Figure 6 shows the enhancement of plant shape for a cabbage, by a similar algorithm to the one described above. As shown in Fig. 6(b), the use of a Sobel operator alone cannot provide an acceptable image with a clear outline. In contrast, our algorithm is capable of providing an image with a clearer outline than that of Fig. 6(b), as shown in Fig. 6(d). This result has been obtained depending on the first standard image, shown in Fig. 6(c). The image obtained, however, is not adequate as a result of numerous fragments. To improve the quality of the image obtained, another standard image, Fig. 6(e), was made and, consequently, provided an image with a more acceptable, clear outline than that of Fig. 6(d).

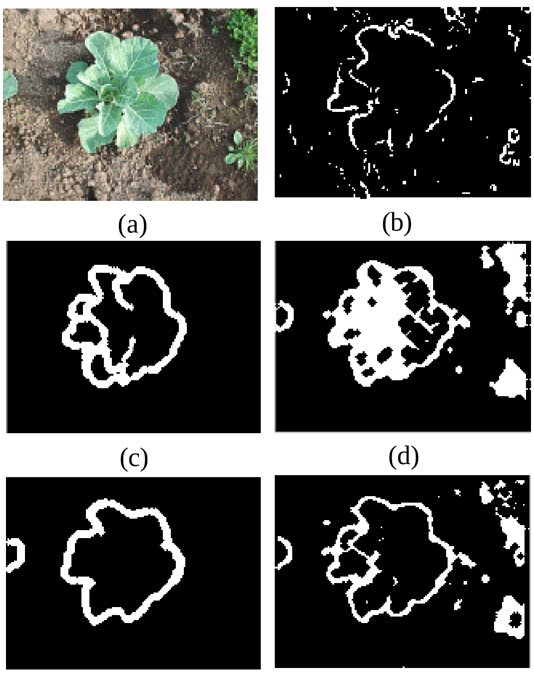


Fig. 6 Result on processing an image of a cabbage plant in a field: (a) an original image; (b) an image processed by EE only; (c) standard image for enhancing the shape of plant; (d) an image processed by the GA dependent on (c); (e) new standard made; (f) processed by the GA dependent on (e).

The filtering operations providing the image of Fig. 6(d) are as follows: TH ranging from 0.25 to 1.0, TB from 0.78 to 1.0, SM, EE, RV and twice iterations of both EF and CF. These results indicate that, in the case of shape enhancement, the expression of standard image sensitively influences the quality of images obtained by the current algorithm.

For investigating the influence of ambiguity in standard images, for the case of area enhancement, the image of a cabbage has processed using standard images shown in Fig. 7(a) and (c), drawn roughly. Figure 7(b) and (d) show images obtained by the current algorithm. The procedure for providing the image (b) has contained TH ranging from 0.40 to 0.53, TB from 0.21 to 1.0, EE, RV and twice of both EF and CF. On the other hand, the filtering operations providing the image (d) has contained TH ranging from 0.24 to 0.77, TB from 0.40 to 1.0, SM, RV and twice of both EF and CF. These results show that area enhancement by the current algorithm is not so influenced by ambiguity of standard images in contrast to shape enhancement. It is considered that, area of target components in images influence validity of fitness evaluation. This is because unfit in the target, which disturbs recognition of the target so much, is evaluated relatively lower than that in the other components if the target area is small.

2.2 Effect of interactive selection

Calculation time for one generation was approximately two minutes in our algorithm, implementing only automatic selection. Since a series of genetic operations, other than those for image processing, requires little calculation time, the time changes depending on filtering operations chosen for each individual. Hence, in order to shorten the entire processing time for obtaining acceptable images, the

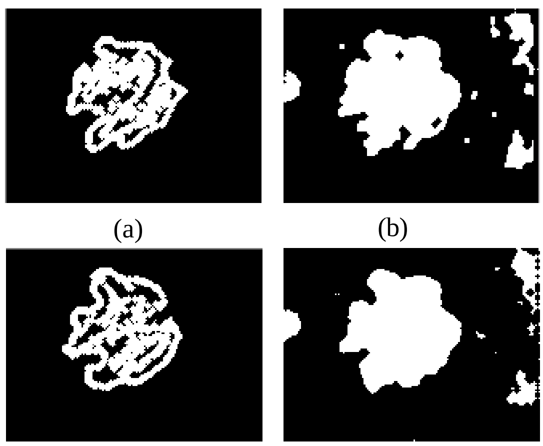


Fig. 7 Processed images, depending on standard images expressed ambiguously: (a) and (b) are standard images; (c) and (d) are the results.

algorithm with interactive selection has been investigated. The algorithm, using the selection method only, did not provided an acceptable image, with respect to area enhancement of the cabbage shown in Fig. 6. This is because the searching space of problems for solutions by visual observation is narrower than that by fitness function. Then, the interactive selection has been used to assist the fitness function. To be concrete, after automatic selection has been used to narrow the search space, interactive selection has been performed. Consequently, the algorithm using both methods provides acceptable images by the 5th generation. In contrast, the algorithm using the automatic selection provides acceptable images only after more than 10 generations.

4. CONCLUSION

Genetic algorithms have been applied for optimizing procedures of image enhancement in this study. The algorithm developed implements several operations for image enhancement, and is capable of optimizing their combination to obtain acceptable images. In addition, we have introduced interactive selection, use of the human ability to cognize a promising individual, into the current algorithm to investigate the effect of human assistance. As a result, the introduction of human cognition has shortened the processing period for acquiring acceptable images. Although neural networks can optimize solutions of various problems, they are not suitable for knowledge acquisition in this case. This is because they cannot show the problem-solving process, and therefore, cannot be controlled by human intention. In contrast, GA incorporates an aspect of parallel computing, and can provide simple expressions for the procedures used. For this reason, it is believed that GAs have the potential to furnish knowledge acquisition system in interaction with human intention. Furthermore, we are sure that the concept of introducing human consciousness into the searching space of problems will constitute a new paradigm in GA applications.

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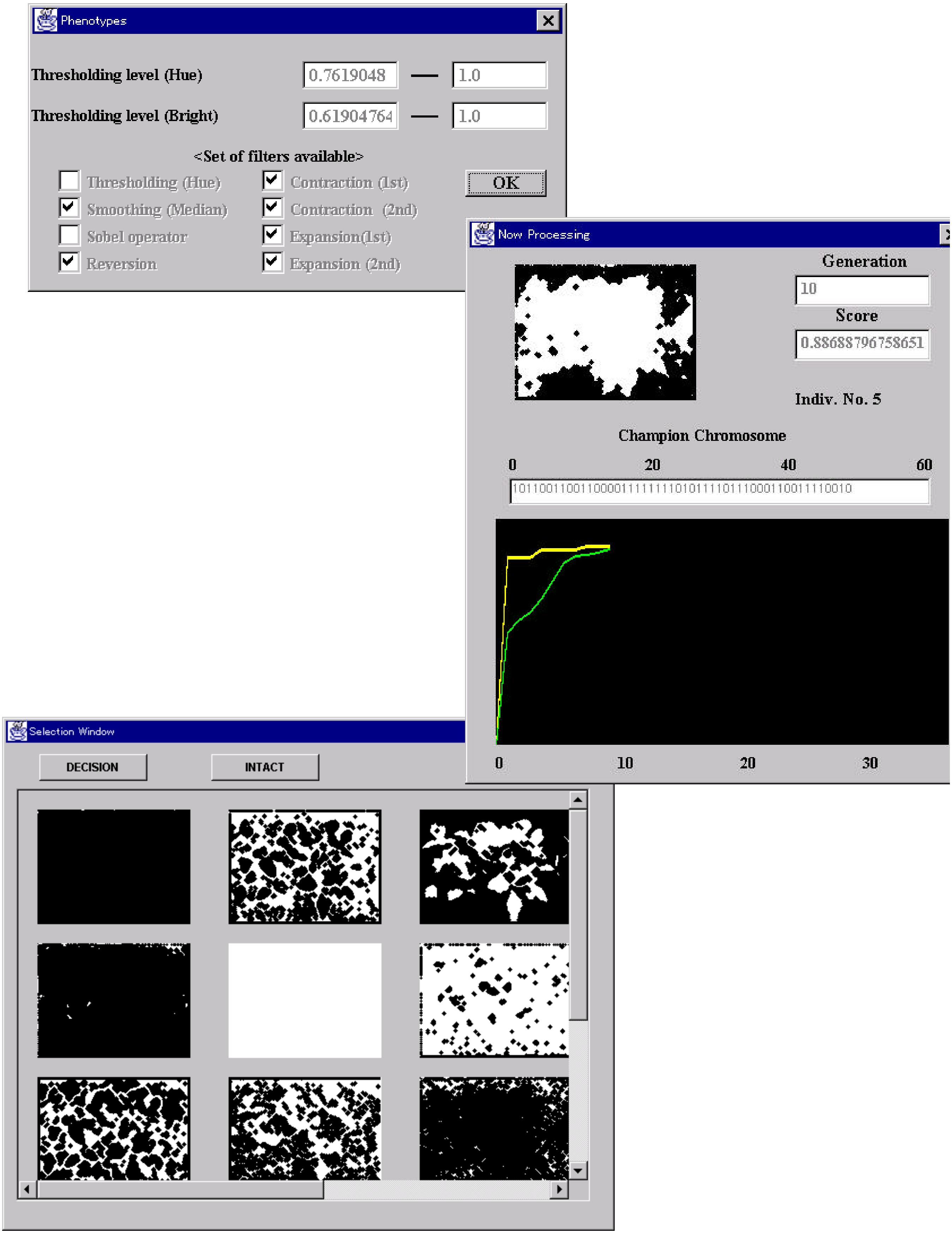
Phenotypes
Thresholding level (Hue) 0.7619048 — 1.0
Thresholding level (Bright) 0.61904764 — 1.0
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Thresholding (Hue)
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