KNOWLEDGE ACQUISITION ON IMAGE PROCSSING BASED ON GENETIC ALGORITHMS

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ABSTRACT

Application software for optimizing procedures ofimage segmentation and for acquiring its knowledge has been developed using Java language. Based on genetic algorithms (GAs), the software searches for the appropriate procedures, such as filtering operations and their parameters, and can segment target components in digital images, compared to rough objective images given by users. Simultaneously, results of the search are stored in a knowledge base on segmenting images taken in various situations, accessed via the Internet using the software. Promising procedures stored in the database are also used for segmentation in response to queries from the software. The software has been tested on segmentation of plant images, commonly used for agricultural studies. Consequently, the combination of the GA and the knowledge base has contributed to rapid convergence of the search for appropriate segmentation procedures.

Keywords;, Genetic algorithms, Java, Knowledge base Segmentation.

1. INTRODUCTION

Easy and immediate acquisition of large numbers of digital color images, for example, of the daily growth of plants in remote fields, has been made possible via the Internet nowadays. 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. Thus, image analysis, segmenting images of objects and deriving their outlines or areas, commonly invokes procedures based not only on routine, but also on trial and error performed by hand.

Automated image processing systems, such as expert systems, have been studied in various areas of engineering. Nazif and Levine [1], Mckeown et al. [2] have studied rule-based expert systems for an automated segmentation of monochrome images, linked to a knowledge base on target components in the images. Those 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 targets. To overcome such difficulty, automated and easy optimization of procedures for image segmentation has been studied [3]. Fortunately, we can conveniently obtain color image data and high performance PCs now. Since color images have considerable information for segmenting targets, the rules for automated segmentation can be simplified.

In this study, we have emphasized the procedures for selecting filtering algorithms and for adjusting their parameters to segment 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 [4] have applied GAs for obtaining optimal image processing transformations mapping the original image of plants, we present application software based on GAs, not only for segmenting images, but also for acquiring knowledge on the operations.

2. METHODS

2.1 Image segmentation strategy

Many kinds of efficient filtering algorithms for image segmentation, such as noise elimination and edge enhancement, have been contrived [5]. Implementing all of them into our algorithms, however, is unrealistic because the increase in operations invokes a proportional

Table1 Filtering algorithms used as phenotypes

Manipulation	Algorithms	Symbols
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.

increase in processing time. Based on our empirical knowledge of the segmentation of plant images, we have selected several filtering algorithms commonly used, and implemented in our algorithm as shown in Table 1. The thresholding and reversion algorithms are performed on a focused pixel of the image processed in serial order, and others have spatial mask operators. While Hasegawa *et al.* [6] has described common procedures for edge enhancement of monochrome images, common procedures to segment targets in color images are considered as shown in Fig.1. The procedures are explained as follows:

- 1) Color of component areas 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 these procedure are carried out, the image processed has been converted to a binarized image with target components defined. In the algorithm, we have adopted not the RGB color model, but the HSI model, because the latter is efficient for the segmentation of plants in fields [7]. All operations are performed after each pixel value is converted from RGB to HSI. 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 the 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 performed, an objective image, 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 remainders are with black ones.

2.2 Genetic algorithms

Chromosomes of the current GA consist of 44 binary strings, assigned to 12 genotypes as shown in Fig.2. Phenotypes corresponding to the genotypes consist of onoff states of the operations mentioned above and parameters for the operations concerning thresholding levels. The minimum thresholding levels on the hue and the brightness coordinates, ranging from 0.0 to 1.0, are encoded with 6 bits. Range of their minimum thresholding levels to the maximum ones is encoded with 4 bits in the same manner. Genotypes of the on-off states are encoded with 3 bits; a decimal value from 0 to 3 is defined as an "off" state of the operation and a value of more than 4 as a state of "on". Such redundant encoding allows sharp

0 – 5		6 – 9		10 – 15			16 – 19	20 - 22	23 - 25
TH (minimum)		TH (range)		TB (minimum)			TB (range)	Toggle of TH	Toggle of SM
26 - 28		29 - 31	3	32 - 34	35 – 37		38 - 40	41 – 43	
Toggle of CF	Т	oggle of CF	Toggle of EF		Toggle of EF	7	Toggle of EE	Toggle 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 a toggle of filtering was encoded with 3 strings.



Fig. 3 Schematic of the knowledge acquisition system, combining GAs and operations for image

changes, caused by one bit reversion, to be avoided.

Figure 3 shows the flow diagram to search for appropriate procedures of the segmentation based on GAs. We have used conventional genetic operations called "simple GA" [8]; crossover at the same points of two neighbor chromosomes, random mutation, and ranking depending on fitness evaluation and selection. At the beginning of the GA operation, chromosomes of a certain population size are generated, initialized with random strings. The crossover occurs at the points of certain string length determined at random, and then, each chromosome is mutated with a certain probability per a string. The each chromosome is interpreted as a sequence of filtering operations and their parameters. Subsequently, a clone of the original image is processed using the each sequence. After the fitness between the objective image and the processed ones is evaluated, the chromosomes are ranked and selected dependent on the degree of the fitness. The procedure from the crossover to the ranking is performed iteratively until appropriate procedures are obtained.

Evaluation and selection play important roles in GAs because they determine the GA's performance of searching for solutions. The function for fitness evaluation 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 as shown in the following formula:

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

where P_{fit} is the number of pixels equivalent between images and P_{unfit} is the number in disagreement. After chromosomes are ranked according to their fitness, chromosomes of the population size, with high fitness in the rank, are selected as parents of the next generation.

2.3 Programming

software, implementing Application genetic operations described above, has been programmed as a stand-alone application for accessing data files stored in local computers, using the Java language. Java has been used so that the software can remain platform-neutral; the software can work on various operating systems. The software consists of three modules; a module for the genetic operations and image processing, user interfaces for setting parameters and for monitoring passage of processing, and a module for connection with a database. Using a drawing interface to make objective images, users can easily select components in the image to be processed and binarize standard images. Passage of the genetic operations is displayed as phenotypes, processed images with the highest fitness and development of the fitness value. Users can input descriptions on targets segmented, and then, the phenotypes, original images and the descriptions are stored through the connection module.

2.4 Database configuration

The knowledge base consists of three-tiered database architecture as shown in Fig. 4. The database has been developed using Sybase SQL Anywhere and Symantec dbANYWHERE, middleware for controlling connection from client PCs to the database via the Internet. Since the connection is managed using a user ID and a password embedded in the software, the database is secured from illegal accesses. A table of the database consists of URL of images, description on features of



Fig.4 Schematics of the knowledge base for image processing based on three-tiered database.



Fig.5 Flow diagram of image processing by two different algorithms.

targets segmented, and procedures obtained for acceptable segmentation.

In conventional image processing systems based on knowledge base, all the data for image processing is gotten ready beforehand. On the other hand, our knowledge base has been made without data at the beginning, and is increasing its knowledge as the software is used for processing various images. Figure 5 illustrates combination in processing by GA search, represented as the block arrows, with that by the knowledge base, represented as the normal ones.

2.5 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 segmentation

An image of soybean plants has been processed to check the algorithm of the software. The software has been implemented on a PC with a Pentium Pro processor (180MHz) and Microsoft Windows NT version 4.0 in the current study. The conditions of the genetic operations performed are 50 of the population size and 0.02 of the mutation rate. An objective image, shown in Fig. 6(b), has been gotten ready beforehand to segment the leaf area of the plants on the original image, Fig. 6(a). At the beginning of the operations, as shown in Fig. 6(c), the procedures with the highest fitness in the generation provided an image far from the objective one. The operations performed in the procedures were as follows; TB ranging from 0.62 to 1.0, SM, RV and twice operations of both EF and CF. The highest fitness in each generation, however, steadily increased as the generation advanced. Figure 6(d) shows the segmented image closest to the objective one, obtained in the 8th generation. These





operations have provided such the acceptable segmentation; TH ranging from 0.21 to 0.41, TB from 0.05 to 1.0, RV and twice iterations of both EF and CF. Those results show that the genetic operations implemented in the software are available to optimize procedures for image segmentation. To provide a segmented image more acceptable than that, elimination operations based on knowledge of targets, for example, regularity of shape and area, would be necessary. The knowledge obtained by the current software, however, will help to make the elimination process efficient.

3.2 Segmentation using the knowledge base

Applicability of the knowledge, procedures for segmentation on various images and targets, stored in the knowledge base, has been investigated. Using the stored procedures, an image of plants in a filed, taken in a situation different from those of the images stored, has been segmented on leaf areas in it. In Fig.7, the image labeled O in the left column is the one to be segmented and the image of its right side is an ideal segmented image, gotten ready beforehand. The images, labeled A, B and C in the left column, are stored with the procedures for segmenting the leaf areas in those images. The procedures have been selected from the database, based on similarity of targets in the images. The images of the right column in the figure are clones of the image O, segmented by the each procedure stored with one in the left column. In the image segmented by the procedure of the image A, the group of plants is segmented successfully. On the other hand, the results by the procedures of the image B and C cannot provide successful segmentation of the plants focused. This result shows that the procedure of image A provides the most successful segmentation. Thus, it has been indicated that procedures in the knowledge base have potential to provide acceptable images segmented on various images rapidly.



Fig.7 Segmentation by the procedures stored in the knowledge base. The images in the right column are the image O, segmented by the same procedures as those segmenting the plant areas in the images A to C.

4. CONCLUSION

We have shown that knowledge of the procedures for acceptable segmentation of color images can be easily obtained using genetic algorithms. Using the software developed, those procedures obtained, simultaneously, can be stored in the knowledge base with images before segmented and descriptions of features on targets. Since the procedures can be used for segmenting different images, the knowledge base can be smarter as various images are processed. In addition, there is no limitation on using the database jointly because the software and the database can jointly work through the Internet. Thus, this architecture has an advantage over conventional expert system approaches, implementing all the knowledge for image processing in the system ahead. In this study, however, we have noticed that there is still great room for improvement in this method. The knowledge base developed cannot be referred easily because procedures must be searched dependently on similarity of features in targets of images processed. Furthermore, automated processing is not established in our architecture since processing by our GA needs objective images made by users. To improve those issues, natural linguistic processing on feature of targets in images and its reasoning architecture will be available.

5. REFERENCES

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