Morphological Image Enhancement Procedure Design By Using Genetic Programming

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ABSTRACT

In this paper, we propose a genetic programming algorithm to design the morphological image enhancement procedure. Given a group of morphological operations and logical operations as function set, this algorithm evolves to produce a rational procedure which can enhance the input images. A novel mechanism which combines the ground truth method and feature significance is brought forward to evaluate the performance of images enhanced by generated procedures. In each generation, the best fitted individuals are selected on the basis of fitness values, and some individuals participate in crossover or mutation with a probability. After each generation, this algorithm outputs the best individual. Seven morphological operations and five logical operations are used in this algorithm. Furthermore, the structuring elements of morphological operations are randomly generated and varied in the whole pattern space. These methods promote the expressive ability of generated procedures. Examined by the binary image feature extraction, the procedure generated by this algorithm is more accurate and intelligible than previous work. In the task of gray scale image enhancement, the generated procedure is applied to infrared finger vein images to enhance the region of interest. More accurate features are extracted and the accuracy of authentication is promoted.

Categories and Subject Descriptors

I.2.8 [**ARTIFICIAL INTELLIGENCE**]: Problem Solving, Control Methods, and Search—*Dynamic programming*; I.4.3 [**IMAGE PROCESSING AND COMPUTER VISION**]: Enhancement—*Grayscale manipulation*

General Terms

Algorithms, Design, Experimentation

Keywords

Genetic Programming, Mathematics Morphological, Image Enhancement, Finger Vein

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1. INTRODUCTION

Digital image processing on computers have been applied to many fields like pattern recognition, robotic vision, biomedical image analysis and biometrics, etc. [21][29][37]. Image enhancement is an important approach in digital image processing, which is a problem-oriented procedure. The goal of image enhancement is to improve the visual appearance of the image or to provide "better" representation for subsequent automated image processing (analysis, detection, segmentation, and recognition) [2]. The methods proposed to enhance image can be generally classified into two categories [2] [3] [10] [11] [28][33] [41]: spatial domain methods, which operate directly on pixels; and frequency (transform) domain methods, which operate on transforms of the image (such as the Fourier, wavelet, and cosine transforms). These methods require expert knowledge to choose right procedure. However, automatic image enhancement is urgent for massive image processing. There are two fundamental factors in automatic image enhancement: automatic image processing procedure and automatic image performance evaluation.

Recently, a variety of evolutionary approaches are applied to the problem of discovering image processing procedure [6] [15] [27] [31]. Most of them concentrate on the image enhancement can be re-framed as filtering problems, and use genetic algorithm (GA) or genetic programming (GP) to produce a set of standard filters [15] [27] [29]. These filter-based GA (GP) methods need complicated formulations which require a large amount of analysis and computation [27].

Mathematic morphological is a powerful non-linear tool for extracting image components, which is useful in the representation and description of region shape, such as boundaries, skeletons, and the convex hulls [11]. Morphological operators aim at extracting relevant structures of the image considered as a set through its sub graph representation, which is achieved by probing the image with another set of the known shapes called *structuring element* [36]. The relevant structures are used to stress objects that we would like and the irrelevant structures are used to suppress either noise or objects, vice versa. The patterns of structuring elements and the morphological sequences are variety. The choice of structuring elements and the operation sequences strongly rely on expert experience and some priori knowledge [25] [26] [35]. Therefore, the morphological operations are suitable tools for evolutionary image processing.

Many researchers use this evolutionary morphological approach to solve problems of image processing. Harvey et al. describe a technique by GA for the optimization of multidimensional gray scale soft morphological filters [13]. They use this technique in the spatiotemporal domain for applications in automatic film restoration. Yoda et al. explore the possibility of obtaining mathematic morphological algorithm for binary images feature extraction by means of GA [40]. In their algorithm, GA is used to search proper operation procedures and only basic mathematical morphology operations — erosion and dilation — are used. This algorithm is restricted to search for fixed length chromosomes and for limited structuring elements in four patterns. Quintana et al. present an approach of morphological binary image analysis based on GP [31][32]. Their algorithms are constructed by logic operators and the basic morphological operators — erosion and dilation. The structuring elements are also manually designed. The GP algorithms evolve morphological operations that convert a binary image into the target image which contain just a particular feature of interest. This work proves that it is possible to evolve good morphological algorithms by using GP. Ballerini et al. introduce a method without a goal image, and the morphological operations are not used for noise reduction or segmentation but for image classification [4]. Their method performs the same operation sequence on images belonging to different classes and tries to find a sequence of operations that keeps unaltered images of one class while changing others. Wang and Tan extend the works of Yoda et al. and Guintana et al. to image enhancement by using GP [38]. This algorithm learns from a section of original image and the corresponding goal image and automatically produces a mathematic morphological operation sequence which transforms the target into the goal.

The common insufficient part of these algorithms is that: because of the complexity of morphological operations, only basic morphological operations (erosion and dilation) are used and the structure elements are restricted in a small set. These shortages limit the expressive ability of morphological operations. Additionally, there is no efficient measure which can be served as a criterion for image enhancement, especially when the image enhancement procedure is used as a preprocessing step for other image processing techniques (detection, recognition and visualization). The use of the statistical measure of the gray level distribution measures of local contrast enhancement (mean, variance, or entropy) have not been particularly meaningful for many images [2].

In this paper, we propose a genetic programming algorithm to design the morphological image enhancement procedure. Given a group of morphological operations and logical operations as function set, this algorithm evolves to produces a rational procedure which can enhance the input images. The objective of image enhancement in our application is to extract more precise and effective features. Therefore, the enhanced result is better when it can be extracted more precise and effective features. A novel mechanism which combines the ground truth method and feature significance is brought forward to evaluate the performance of images enhanced by generated procedures. In each generation, the best fitted individuals are selected on the basis of fitness values, and some individuals participate crossover or mutation with a probability. After generations' evolution, this algorithm output the best individual. Seven morphological operations and five logical operations are used in this algorithm. Furthermore, the structuring elements of morphological operations are randomly generated and varied in the whole pattern space. This paper is organized as follows. The genetic programming algorithm we proposed is presented in Section 2. The experimental results of binary images feature extraction and gray scale image enhancement are described in Section 3. Finally, the concluding remarks of this paper are drawn in Section 4.

2. PROPOSED GP ALGORITHM

The genetic programming provides an approach to find a computer program to solve a problem [19]. One of the key features of the proposed GP algorithm is that it uses tree structure representations to solve the image enhancement problem. There are two major tasks in the GP loop: fitness function definition and genetic operators which select the best individuals and reproduce next generation in a probabilistic way. Details of GP can be found in [12][19]. The prototype of proposed algorithm is illustrated in Alg.1. The initiated population is generated randomly by growing [19] and the length of individuals is distributed homogeneously. In each generation, an automaton decodes each individual to operation sequences, executes the operation sequences, outputs result images, and evaluates fitness values.

Algorithm 1 Proposed GP algorithm

```
Initiate population;
while  less than MAX generations do
    for each individual do
        Execute the operation sequence and get result image;
        Calculate fitness values;
    end for
    Sort individuals by fitness value;
    Selection;
    Crossover;
    Mutation;
end while
Output best individual;
```

2.1 Function set and terminal set

We use two types of operations in the function set, morphological operations and logical operations. For consistency, only the operations with two operands are chosen, which will be the inner nodes. The morphological operations take an image and a structuring element as operands and output an image. The logical operations take two images as operands and output an image. There are two types of leaf node in the terminal set, the original image and the structuring elements. The second operand of a morphological operation must be a structuring element. Fig.1 shows a small piece of program with the function set and terminal set. *IMG* means the original image which is the input image of this individual and the meaning of other signs will be introduced in following sections.

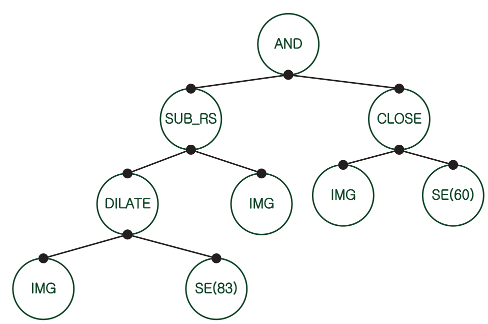

Figure 1: The tree style illustration of a short peace of procedure: (AND (SUB_RS (DILATE IMG SE(83)) IMG) (CLOSE IMG SE(60)))

2.1.1 *Logical operations*

Five logical operations are used in this algorithm, *AND, OR, XOR, SUB* and *SUB_RS*, all of which have two operands. All the two operands are images which can be either the original image or the output of other operations. The outputs of the logical operations are images. The definition of the logical operations is shown below and the semantic of these operations in binary images are the same as in gray scale images [5][36]:

- *AND*, each point takes the minimum gray scale of corresponding points in two images.

$$A \cap B = \min(A, B) \tag{1}$$

- *OR*, each point takes the maximum gray scale of corresponding points in two images.

$$A \cup B = \max(A, B) \tag{2}$$

- *XOR*, can be defined from upper operation.

$$A \oplus B = (A \cup B) - (A \cap B) \tag{3}$$

- *SUB*, can be defined from upper operation.

$$A - B = A - (A \cap B) \tag{4}$$

- *SUB_RS*, can be defined from upper operation.

$$-A + B = B - (A \cap B) \tag{5}$$

2.1.2 Morphological operations

We use seven morphological operations in this algorithm. Each operation has two operands, one is a image and the other is a structuring element.

The basic morphological operations are erosion and dilation. In a binary image, the eroded set is the locus of points where the answer to the question "Does the structuring element fit the set?" is affirmative [36].

$$\epsilon_B(x) = \{x | B_x \subseteq X\} \tag{6}$$

Here, B is a structuring element. The dilation is the dual operator of the erosion, and the dilated set is the locus of points where the answer to "Does the structuring element hit the set?" is affirmative.

$$\delta_B(x) = \{x | B_x \cap X \neq \phi\} \tag{7}$$

Erosion and dilation are the letters of the morphological alphabet. These letters are then combined to create the words of the morphological language. Complex morphological operations, such as morphological gradient, morphological opening, morphological closing, top-hat and black-hat [11] [36], can be composed of erosion and dilation. These operations are all used in this algorithm.

The erosion and dilation operations in a gray scale image may be different from ones in a binary image. In a gray scale image, the eroded value at a given pixel x is the minimum value of the images in the window defined by the structuring element when its origin locates at x:

$$[\epsilon_B(f)](x) = \min_{b \in B} f(x + b) \tag{8}$$

The dilated value at a given pixel x is the maximum value of the image in the window defined by the structuring element when its origin is at x:

$$[\delta_B(f)](x) = \max_{b \in B} f(x + b) \tag{9}$$

Accordingly, the meaning of morphological gradient, morphological opening, morphological closing, top-hat and black-hat in gray scale image is also changed.

Yoda et al. [40], Quintana et al. [31] and Wang et al. [38] all choose structuring elements manually. Their algorithms select structuring elements in a small set. Actually, the pattern space of structuring elements is huge ($2^{n \times n}$, n is the size of the pattern) and manually chosen structuring elements only cover a small part of the whole pattern space. In this algorithm, we use the structuring elements with size 3×3 which covers the whole 3×3 pattern space. Without losing generality, the values at the position (2, 2) of all patterns are fixed to 1 . Therefore, each structuring element can be denoted by a 8 bits integer. Each bit of the integer represents the value of the pattern at corresponding position. Equ.10 shows the mapping between a 8 bits integer and a structuring element. Let $SE(integer)$ denote the structuring element represented by integer in other parts of this paper.

$$SE(95) \Rightarrow 01011111 \Rightarrow \begin{pmatrix} 010 \\ 11 \\ 111 \end{pmatrix} \Rightarrow \begin{pmatrix} 0, & 1, & 0 \\ 1, & 1, & 1 \\ 1, & 1, & 1 \end{pmatrix} \tag{10}$$

2.2 Genetic operators

Genetic programming gives each individual a probability to being selected to participate the operations: reproduction, crossover and mutation [19].

The reproduction operator selects the favorable individuals on the basis of their fitness values and copies them into the new population.

Crossover operator is performed by exchanging sub-trees randomly chosen from two individuals to generate two new individuals into the new population [19][30].

Mutation operator randomly changes individual [19]. The operation of mutation consists of two steps. Firstly, a single node of the individual is randomly selected. Next, this node is randomly changed without violating semantic. If randomly chosen node is a logical/morphological operation, then it can only be randomly changed to other logical/morphological operation, respectively. If randomly chosen node is a structuring element, then it can only be randomly changed a bit.

2.3 Fitness function

In the evolution, the fitness function evaluates all the individuals and selects potential individual to reproduce next generation. It is important to define a suitable image enhancement measure for the evaluation. "There is no universal measure which can specify both the objective and subjective validity of the enhancement method" [3][17] In this algorithm, we need an automatic method to evaluate the effectiveness of image enhancement. Previous measures are based on the human visual, some researchers use contrast of image [28], others use entropy as image enhancement measure [2][3]. However, when we test our algorithm by method in [3], a number of images show no consistency using these statistical measurement, which clearly shows an improved contrast. The actual reason of this situation is that the mathematic morphological operations have strong power to modify the image to fit the evaluation method.

Therefore, we conclude that the evaluation measure should be correlative to the application. In this paper, the objective of image enhancement is to extract more precise and effective features. Consequently, the enhanced image from which more precise and effective features can be extracted is better. Let f_i and f_j denote different enhancement procedure. Let $\theta(f_i, I)$ denote the execution of f_i on image I. Let δ denote the feature extraction operation, including threshold and thinning. Let ϕ and φ denote the evaluations of image and feature extraction, respectively. Accordingly, we get this conclusion:

If $\varphi(\delta(\theta(f_i, I))) > \varphi(\delta(\theta(f_j, I)))$, then $\phi(\theta(f_i, I)) > \phi(\theta(f_j, I))$, and consequently, f_i is better than f_j.

Thus, we evaluate the performance of the extracted feature under same threshold and thinning methods instead of evaluating the performance of image. We borrow ideas from the evaluation of edge and ridge detection methods. To evaluate the performance of edge detection methods, Heath et al. organize them into three categories: theoretical evaluation, evaluation using ground truth and evaluation without ground truth [14]. A theoretical evaluation is done by applying a mathematical analysis without the algorithm ever being applied to an image [1]. The basic idea of ground truth approaches is to measure the difference between the detected edges and the ground truth. The third category methods evaluate the form of the edges and the likelihood of a detected edge being a true edge given the local edge pixel intensities. Kitchen and Rosenfeld develop a method by the local edge coherence [18]. Lowe develops a concept *significance* to evaluate a straight line, which can be estimated by calculating the ratio of the length of the line segment divided by the maximum deviation of any point from the line [24]. This means the detected line is better if it is longer and straighter. Furthermore, this measure is also in accordance with common sense of people about edge detection. Rosin et al. separate edges into lines and arcs and evaluate them with significance [34]. Lindeberg uses this concept to evaluate edge and ridge delectation [22][23].

The evaluation of significance needs not the ground truth result and suit for the automatic evaluation. However, the strong expressive ability of the mathematic morphological operations is prone to modify the image to fit the evaluation method. Thus, we must define a anchor to hitch the enhancement method, which will restrict the modification in a tolerant range. Finally, we design a evaluation function combines the ground truth and significance which could not only take the advantage of objective evaluation but also avoid over-modifying. Firstly, we manually calibrate the ground truth result of the input image and use the Modified Hausdorff Distance (MHD) [8][16] to measure the similarity of extracted feature image and ground truth result. Given two finite point sets $M^p = m_1^p, m_2^p, ..., m_k^p$ (representing a model image) and $T^p = t_1^p, t_2^p, ..., t_k^p$ (representing a test image) of two images, MHD is defined as

$$H(M^p, T^p) = \max\left(h(M^p, T^p), h(T^p, M^p)\right) \tag{11}$$

where the superscript *p* stands for point in image and

$$h(M^p, T^p) = \frac{1}{N_m^p} \sum_{m_i^p \in M^p, t_j^p \in T^p} min \| m_i^p - t_j^p \|, \tag{12}$$

and N_m^p is the total pixel number in the image.

Next, we compute the significance of extracted features. We use the quadratic fitting to fit the extract features, since we expect extract features are curves which is smooth and continuous (Alg.2).

Algorithm 2 Significance(image)

```
S = 0;
find all curves in image;
for each curve do
    compute its length L;
    compute its Quadratic fitting;
    compute the variance V;
    S = S + V/L;
end for
output S;
```

Finally, we combine these two indexes into a fitness function 13. For consistency, these indexes are normalized to $0 \sim 1$.

$$F(I, G) = (1-\lambda)\frac{1}{H(I, G) + 1} + \lambda\frac{1}{S(I) + 1} \tag{13}$$

, where I stands for the extracted feature image, G for the ground truth image, H for MHD, S for Alg.2, and $0 \leq \lambda \leq 1$.

The MHD part of the fitness function represents the closeness of the extracted feature image to the ground truth result, and the Significance part represents the expecting of good feature — continuous and smooth. Because of the strong modifying ability of mathematic morphological operations, the Significance part should be very small in this function, λ is used to adjust the weights of these two parts, as our experience, $0.01 \leq \lambda \leq 0.05$ is suitable.

3. EXPERIMENTAL RESULTS

We conduct two experiments to verify our algorithm. Firstly, we apply this algorithm to the feature extraction in binary image, which has been used by former researchers, for checking its expressive ability. Next, we apply this algorithm to the gray scale image enhancement for checking the effectiveness.

3.1 Experiment on artificial binary images

As Quintana et al. [31] and Wang and Tan [38], we also use an artificial data set composed by four features: squares, disks, rings and stars. Four images are generated by randomly choosing distributed position of 50 features, and each image contains one type of the four features, defined as the target images. All four target images are overlaid to obtain the source image. The objective of our GP algorithm is to generate the procedures to extract expected objects from the source image. The size of these images is 640×480. The source image is shown in Fig 2. The features randomly distributed in the source image may overlap, which makes the detection more difficult.

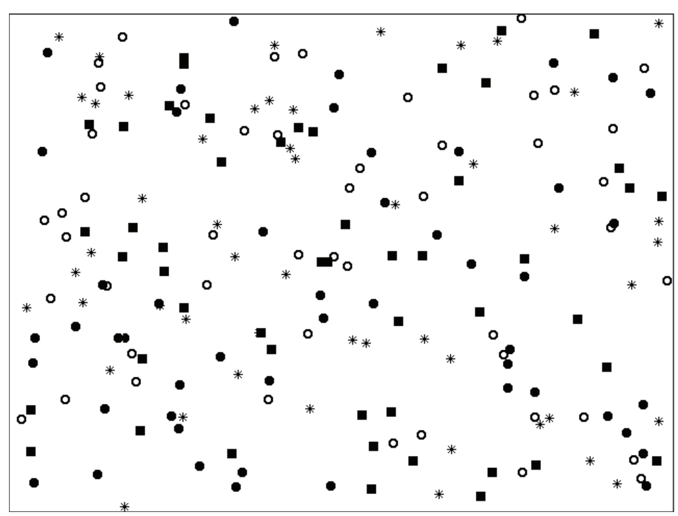

Figure 2: Random generated artificial objects image.

For comparison, we use the fitness value which was used in [40], [31] and [38]. The objective fitness function $F(0 \leqslant F \leqslant 1)$ is known as similarity as the correlation coefficient between a processed image and the goal [40].

$$F = \frac{(f \cdot g)}{\sqrt{(g \cdot g)} \times \sqrt{(f \cdot f)}} \quad (14)$$

, where f and g are two binary images of size $M \times N$ and

$$(f \cdot g) = \frac{1}{M} \cdot \frac{1}{N} \sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j) \cdot g(i,j) \quad (15)$$

,image f is the processed result, and image g is the goal.

Since in a binary image the white pixels represent objects, this seems a reasonable choice of fitness function. The optimum is $F = 1$ when all the pixels match. The worst case is $F = 0$ when none of the pixels match [40].

We select a small area from the source image which contains all four features as the source of the training set, whose size is 100×100 (Fig.3). The corresponding areas on the target images are also selected as the learning goals.

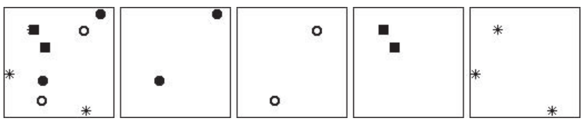

Figure 3: From left to right: learning source; learning goals — disks, rings, squares, stars.

Table 1: Parameters for artificial objects extraction

Parameter names	Values
Population size	4096
Generations	100
Max Nodes	48
Reduction Probability	0.25
Crossover Probability	0.5
Mutation Probability	0.25

Table.1 lists the parameters we used in this experiment. We execute this algorithm four times on this training set — each time with one feature. This algorithm produces four procedures which can extract one of the four features. Fig 4 shows the best fitness values of each generation in the training course. The extraction of disk, ring and square quickly converged at 1, and the extraction of star is also converged close to 1.

There is a procedure to extract *disk* features generated by this algorithm(IMG denotes the original image):

$(\ AND \ (\ SUB\_RS \ (\ DILATE \ (\ DILATE \ (\ OPEN \ (\ OPEN \ (\ GRADIENT \ (\ SUB \ IMG \ (\ XOR \ (\ CLOSE \ (\ GRADIENT \ (\ DILATE \ (GRADIENT \ IMG \ SE(99) \ ) \ SE(38) \ ) \ SE(45) \ ) \ SE(110) \ ) \ (ERODE \ IMG \ SE(114) \ ) \ ) \ ) \ SE(110) \ ) \ SE(74) \ ) \ SE(108) \ ) \ SE(83) \ ) \ SE(83) \ ) \ IMG \ ) \ (CLOSE \ IMG \ SE(60) \ ) \ )$

We apply these four procedures on the source image to extract these four features separately and measure the extracted results with the target images by the fitness function. Executing this methods for 10 times, we get the mean performance of our GP algorithm and compare this performance with Quintana et al.'s and Wang and Tan's (Table. 2). In the extraction of all the four features, our algorithm shows the best performance. By the definition of fitness

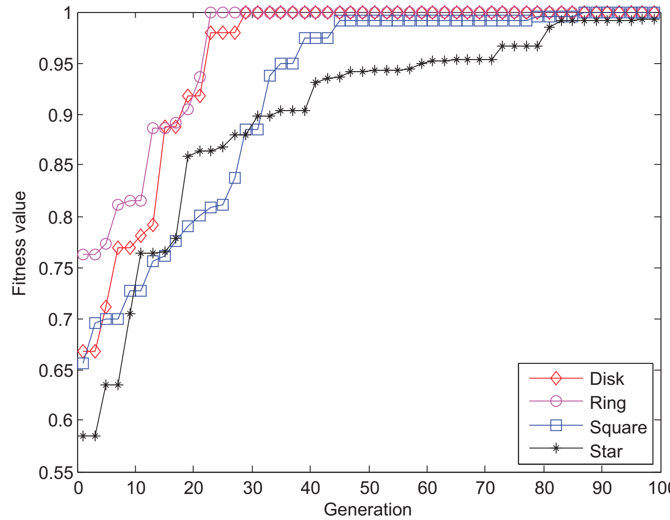

Figure 4: The fitness values of each feature in the evolution progress.

value, the result is the proportion of correctively extracted feature pixels. Considering the overlap of features, the proposed GP algorithm has a strong expressive ability.

Table 2: Comparison of artificial objects extraction

Feature	Our Alg.	Wang et al.[38]	Quintana et al.[31]
Disks	**0.986**	0.982	0.868
Rings	**0.938**	0.8583	0.906
Squares	**0.996**	0.990	0.870
Stars	**0.961**	0.959	0.922

Quintana et al.'s algorithm has the heaviest computational load. They use a Linux cluster with one master node (CPU dual Intel Xeon 2 GHz, 2 GB Memory) and 22 client nodes (CPU Dual Athlon MP 1900+, 1.6 GHz, 1 GB Memory) in their experiments [31]. Wang and Tan use a PC (CPU Intel Core Duo T9400 2.53 GHz, 4 GB Memory) and the execution time for each feature is in several minutes [38]. We use a PC (CPU Intel Core Duo E4500 2.20GHz, 6 GB Memory), implement the algorithm with C++, and the mean execution time of each feature: disk / 504s, square / 941s, ring / 172s, star / 1268s.

3.2 Experiment on gray scale image

In this experiment, we apply this algorithm on the enhancement of the gray scale image. There are 1898 low quality finger vein images collected by an infrared CCD device, which contains 328 fingers — each finger has 4 to 6 images. We use this algorithm to generate a procedure to enhance these images and exam the effect. This experiment is consists of four steps:

1. randomly choose four images from the data set as the learning samples, then calibrate the corresponding feature images manually as the learning goals;

2. execute this algorithm on selected images with different parameters to generate the image enhancement procedures;

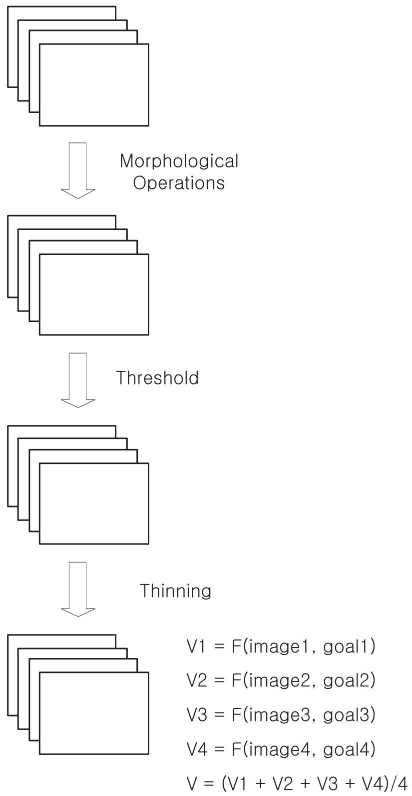

Figure 5: Compute the fitness value for an individual.

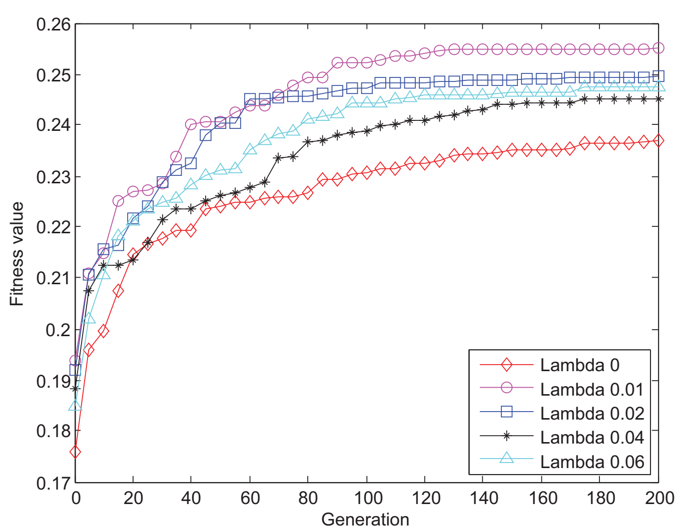

Figure 6: Best fitness values of each generation for different λ.

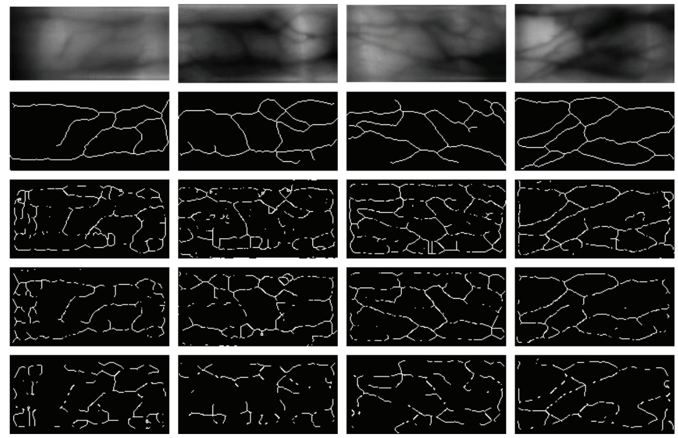

Figure 7: From top to bottom: original images; manually calibrated goal images; features extracted without enhancement; features extracted with GP generated procedure enhancement at $\lambda = 0$; features extracted with GP generated procedure enhancement at $\lambda = 0.01$.

3. use the generated procedures to process the images respectively;
4. compare the identification rates of the features extracted from processed images by different procedure.

We use the fitness function defined in Equ.13. The method of computing fitness value is illustrated in Fig.5 and for each individual:

1. apply it on the four images;
2. threshold previous results into binary images to get features [7];
3. thinning the features to skeletons [20];
4. compute the fitness value for each image with Equ.13, and let the mean of these values be the fitness value of this individual.

The parameters of the GP program used in this experiment is shown in Table.1. According to previous analysis about λ in Equ.13, we use different λ in fitness function for several executions, results are shown in Fig.6..

We can draw conclusions from Fig.6:

- The fitness values of all five varying parameter setting of λ are promoted after 100 generations evolution. This indicates that the proposed procedure affects the promotion of feature extraction.
- The fitness values of four parameter setting of $\lambda > 0$ are all better than $\lambda = 0$, which means the Significant part of fitness function contributes to effective evolution. In addition, the smaller λ shows better performance and the best performance procedure is at $\lambda = 0.01$.

Fig.7 shows the executing results of this algorithm. The images in the fifth row are features extracted after the generated procedure with $\lambda = 0.01$, which are more precise and closer to images in the second row and have fewer noises.

Next, we apply the procedures obtained on the whole data set to compare the identification rate. We get six groups of feature images with these procedures: features extracted without enhancement, extracted features of enhanced images by the generated procedure at $\lambda = 0$, $\lambda = 0.01$, $\lambda = 0.02$, $\lambda = 0.04$ and $\lambda = 0.06$. We use the false acceptance rate (FAR) to evaluate the performance of each group. FAR is the most commonly used measure of identity authentication, which is the fraction of access attempts by an un–enrolled individual that are nevertheless deemed a match [39]. We use the Modified Hausdorff Distance (MHD) [8] to measure the similarity of two images. The classifier is Nearest Neighbor [9] and the experimental strategy is Leave–One–Out. We execute these steps ten times and get the average values, illustrated in Fig.8.

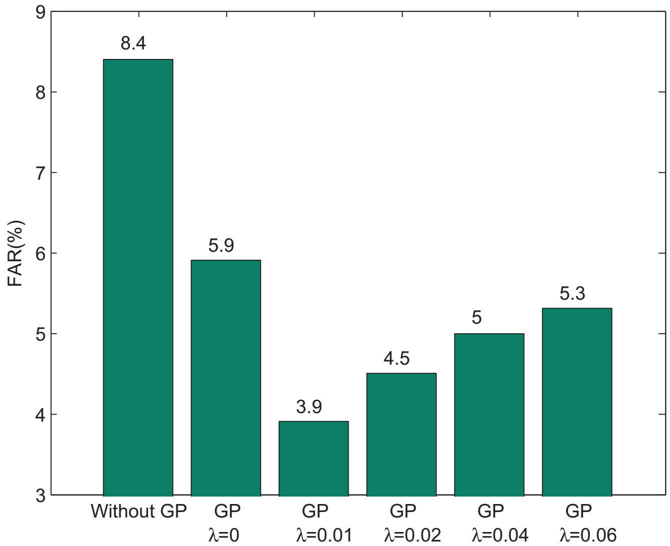

Figure 8: Comparison between FAR of feature extraction without GP enhancement and FARs of GP enhancement with different λ .

The FARs of the generated procedure with varying parameter setting are smaller than the result without GP enhanced. The best performance is shown at $\lambda = 0.01$. This indicates that the finger vein images processed by the morphological procedure generated by using the proposed GP algorithm can be extracted more precise features, which means the objective of image enhancement by G-P achieves. We conduct this experiment on the same platform as previous one. The computational complexity of the GP algorithm is huge which need about 2 hours for 100 generations. However, when this algorithm applied to real state work, we only do this work once to get the best procedure which then can be used on the whole data set. The average time of the procedure to process a image is 0.005s.

4. CONCLUSION

For a long time, researchers explore for automatic generating image processing method. The shortage of effective operating method and the absence of objective evaluation method postpones the application of this approach. In this paper, we propose a genetic programming algorithm to design the morphological image enhancement procedure. The combination of morphological operations and logical operations shows strong expressive ability. The automatic evaluation mechanism let the genetic programming algorithm generate effective morphological procedure. Examined by the binary image features extraction, the procedure generated by this algorithm is more accurate and intelligible than previous work. In the task of gray scale image enhancement, the generated procedure is applied to infrared finger vein images to enhance the region of interest. More accurate features are extracted and the accuracy of authentication is promoted.

5. ACKNOWLEDGEMENT

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