

SHAPE EXTRACTION OF MEDICAL OBJECTS VIA THE EVOLUTION OF GRAY-SCALE MORPHOLOGICAL SEQUENCES

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ABSTRACT

In this paper, an evolutionary method utilizing gray-scale morphological structures is proposed for object shape extraction. Artificial individuals are built up from gray-scale operator sequences by randomly choosing structuring elements from a basic operator pool. These individuals are mapped to list-like data representation structures and are manipulated by recombining or changing parts of the operator sequences randomly chosen. The extracted objects are obtained by carrying out the filtering with the best fit individual and calculating a residue image. The normalized correlation of the filtering results and the contributed input image areas is calculated for fitness. This method requires no preliminary knowledge of the object shape and also no constraints are used for image background and contrast. The evolutionary approach provides global and directed search on large number of possible morphological sequences and a method that can be applied on a wide range of images. The morphological operations are implemented by low level image processing steps such as image shifting and min-max operations and executed as parallel tasks on a multiprocessor basis by applying both data and algorithmic parallelization. As an example, this method is applied to the shape extraction of blood vessels in a system consisting of a camera device connected to a grid of transputer nodes.

1. INTRODUCTION

Considering the number of people who suffer thrombosis and blood vessel narrowing (stenoses) and are constrained to undergo surgery in each year, we can easily understand the great importance of a diagnostic tool for preventing these diseases. As a core function, this tool requires a fast automatic method for determination of the shape and network of blood vessels locating in the upper layers of the human skin such as in the corium and subcutis on arbitrarily chosen skin areas. Automatic detection of the shape of objects is a fairly complicated task. Classical methods like linear filtering and simple segmentation can not be applied, especially in the presence of noise, changing image background, low contrast etc. Using morphological operators[1], the objects of interest in the image can be analyzed directly through their geometrical features. One of the most important characteristic of morphological methods is that they require the exact specification of the structuring elements. In order to use morphological operators effectively and in order to preserve the original shape of the objects in the presence of noise, multiple structuring elements and repeated operations have to be applied

in most cases. Examples of using iterative morphological operators by multiple structuring elements for eliminating noise can be found in the literature[2]. The selection of the structuring elements and the way they have to be combined to perform an effective morphological filtering are usually achieved by a trial approach. Also, the obtained method is usually specific to a certain application. A general method for morphological filter design is proposed by Song and Delp[3] where they apply union of openings and intersection of closings by four lines and L shaped structuring elements. Considerable effort has been made to decompose complex structuring elements. Zhuang and Haralick[4] proposed a tree-search algorithm for n-point decomposition of binary structuring elements. This algorithm was later extended to the decomposition of arbitrary gray-scale structuring elements by Camps, Kanungo and Haralick[5] by applying a simple search on a finite set of values. The purpose of these decomposition algorithms is to simplify the calculation and consequently the cost of computation and also to help the implementation of morphological operations by hardware. All of these techniques are very helpful in understanding the behaviour of various kinds of morphological operators, however it is rather difficult to automatically design effective morphological operators suitable for direct object extraction. There has been several types of gray-scale filters[6] constructed to filter out noise, determine edges or embedded areas contributed to uni-level regions such as flat filters, top-hat filters, morphological gradient filters etc. Also a powerful morphological segmentation method has been developed by Meyer and Beucher[7] where they apply a flooding method on gradient watersheds. Applying one of these gray - scale filters or their combinations can avoid the errors emerging during binarization, however the problem of the structuring element selection still remains unsolved.

In this paper, an evolutionary method[8] utilizing gray-scale morphological structures is proposed for object shape extraction. Artificial individuals are built up from gray-scale operator sequences by randomly choosing structuring elements from a basic operator pool. These sequences are mapped to list-like data representation structures and manipulated by recombining or changing parts of the operator sequences randomly chosen. The object shape is obtained by carrying out the filtering with the best fit sequence of morphological operators on input image regions and calculating a residue image. The normalized correlation of the filtering results and the contributed input areas is calculated for fitness. This method requires no preliminary knowledge of the object shape and also no constraints are used for image background and contrast. As an example, the method is applied to the detection of the shape of blood vessels located in upper skin layers. This approach uses no constraints on image

background and contrast and also no preliminary information of vessel shape is necessary. Unlike other imaging techniques that mainly uses angiograms as input, in this work infrared filtered images taken by CCD camera are used for input. Vessels of arbitrary size skin areas can be investigated by taking these pictures that would be difficult by using computer tomography, magnetic resonance or ultrasonic imaging techniques, because it is difficult and time consuming to obtain cross sections in few mm wide intervals on broad skin regions. We use a camera device connected to a parallel architecture of transputers in order to obtain a fast and low cost system.

2. EVOLUTION OF GRAY-SCALE MORPHOLOGICAL SEQUENCES

Evolutionary methods, first introduced by Holland[8] are based on the theory of Darwinian evolution and model the selection and reproduction processes occurring in the nature in order to find solutions for complex scheduling and optimization problems. In this paper we use this type of modeling for our shape extraction problem.

We take a gray-level digitized image as input. In this method, gray-scale morphological structuring elements of different size are used as features. Each artificial individual acting as a solution of the shape extraction problem consists of a morphological operator sequence. A starting population of individuals is created by generating sequences of structuring elements of a maximum size of 5x5. This process is carried out by selecting structuring elements from a basic set of flat-type, ball-type, disk-type, pyramid-type, diamond-type, Gaussian-type etc. structuring element pool randomly. These individuals are mapped to data objects consisting of list structures that are built up from two-dimensional arrays each corresponding to a structuring element in a given sequence. The information carried by an individual such as by a morphological sequence is stored in a series of two dimensional arrays in order to keep the two dimensional characteristic of the structuring elements. The operators then act on areas of the input image and each individual is evaluated to give a measure of its fitness. Beside the representation of individuals to choose an appropriate fitness function is another key issue for this algorithm, because the convergence of the method highly depends upon this function. This fitness value is defined as the normalized correlation between the regions of the filtered binary image and the corresponding regions of the original image.

$$nc = \frac{\left[N \sum_i I_i F_i - \left(\sum_i I_i \right) \left(\sum_i F_i \right) \right]}{\sqrt{\left[N \sum_i I_i^2 - \left(\sum_i I_i \right)^2 \right] \left[N \sum_i F_i^2 - \left(\sum_i F_i \right)^2 \right]}} \quad (1)$$

where

N is the total number of pixels

I_i is an image pixel

F_i is the corresponding pixel in the filtered binary image .

The filtered image is obtained as the result of morphological openings carried out by the structuring element sequence encoded in a given individual. This can be expressed as the following[3]:

$$G = \max_{i \in (1, \dots, n)} (I \circ k_i) \quad (2)$$

where

I is the input image, k_i is a structuring element in the given sequence and n is the length of the sequence.

Then a binary image is calculated by thresholding the residue image which is obtained by taking the pixelwise difference between the filtered and the original image data. The threshold value is automatically determined from the histogram of the residue image by detecting the global and local minimas of the histogram. Also, this threshold value can be used as a part of the individuals and can be involved in the genetic method. Using the information of fitness, a selection process is carried out next to provide a set of individuals that will be manipulated for producing offsprings. This selection is accomplished in a roulette wheel-like fashion[9] by calculating the selection probability distribution on the basis of the fitness values and the selected individuals are put into a buffer for further processing. Two type of genetic operators are defined for manipulation: a unary type mutation and a higher order crossover. For both operators, first a randomization is carried out to give a probability of undergoing manipulation to each selected individual and then the selected individuals are fed into a buffer. The crossover is implemented in two steps. In the first step, a location number in the structuring element sequence and then a crossing point as a location in the two dimensional structure of that element are chosen. The crossover is accomplished by changing the counterparts of the two sequences. The mutation is accomplished by applying a change in a given structuring element. This is carried out in two ways also. In the first way, a selected structuring element in the sequence that is randomly chosen for mutation is changed to another type of structuring element chosen also randomly from the basic pool. In the second way, the gray levels of the element are altered. This two ways are also applied on a random basis. The pairs of individuals that has to be selected to carry out the recombination are selected randomly as well.

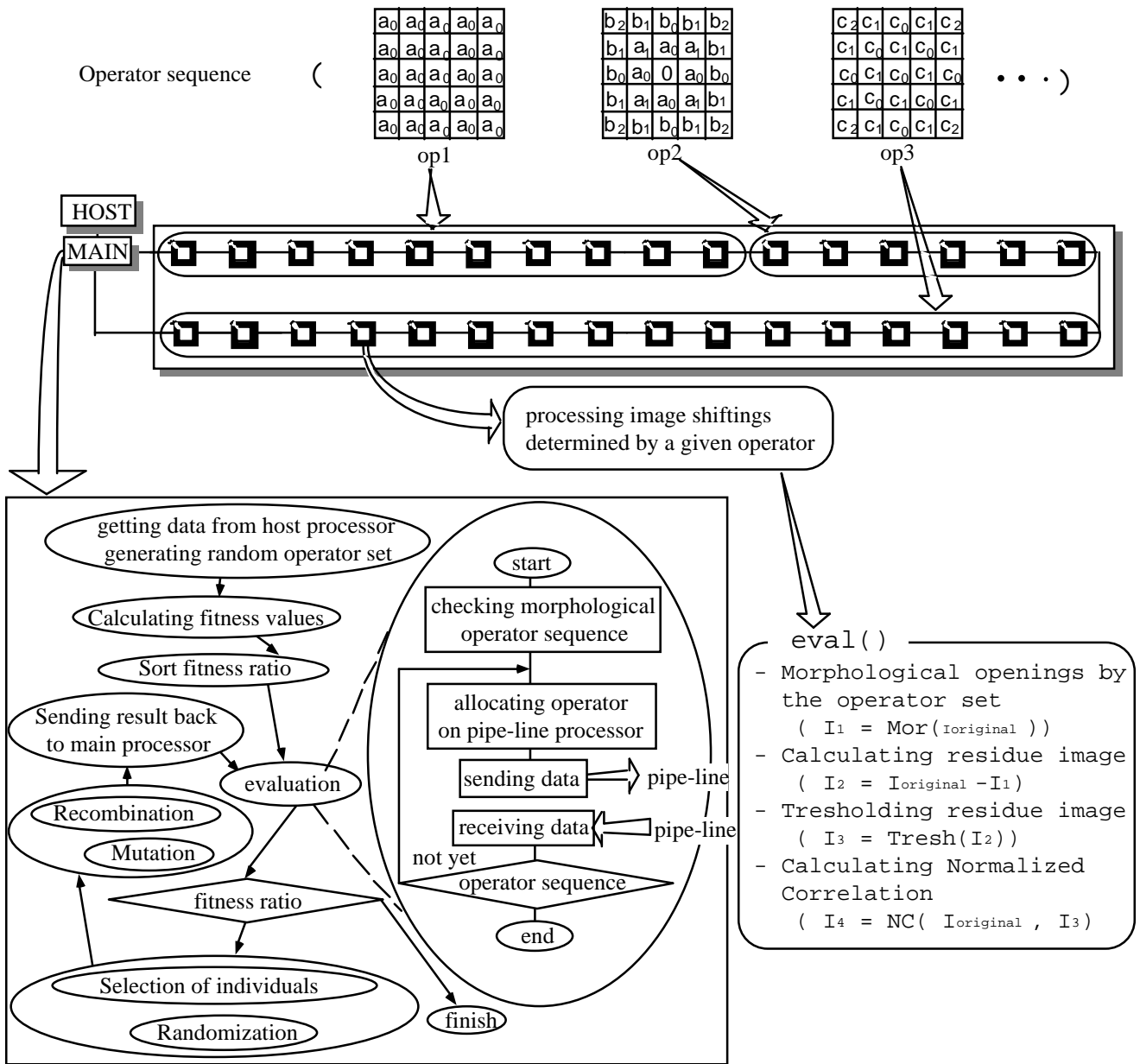


Fig. 1. Outline of the calculation

After finishing the recombination and mutation processes, a replacement strategy has to be decided in order to generate a new population. Here we used a partial replacement strategy. A new generation is created by replacing the less fit part of the population with the newly generated individuals. The replacing ratio is determined on the basis of the fitness distribution and it is usually between 0.3 and 0.5. The rest of the algorithm is just repeating the evaluation, selection and manipulation processes in a cycle until either the required fitness is reached, or no more progress can be measured.

3. PARALLEL IMPLEMENTATION

The method is implemented parallel on a multiprocessor system, consisting of a grid architecture of 32 T800 transputers[10]. The system is supervised by a main transputer node that is also a T800 one and that is directly connected to the host computer.

The parallel implementation of this calculation is based on the special characteristic of the morphological operations. The image data are first split into small two dimensional regions and are loaded to the main transputers extended memory space.

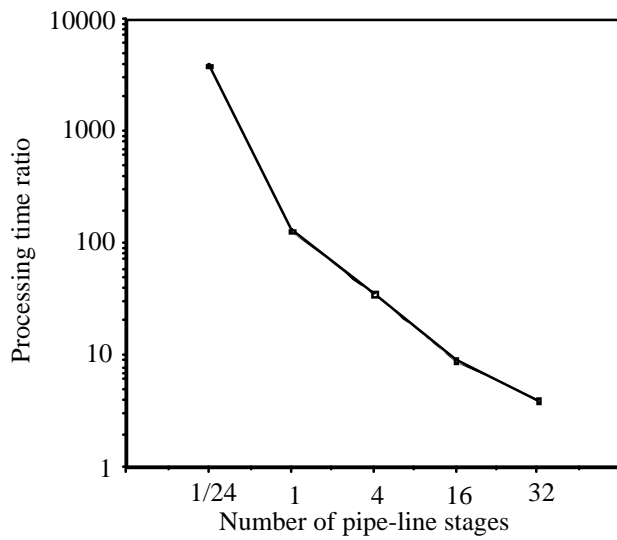


Fig. 2. Processing time vs. pipeline-stages

The morphological operations are implemented by image shifting, minimum and maximum calculations and can be processed independently. A single morphological operator can be expressed by a 5x5 array in our case. The shifting directions are determined by 24 elements of a given operator. To carry out these independent steps parallel would be resulted in an 24 times speedup when accomplishing the processing on a given operator. However, we have a series of operators to be applied in a sequence. To accomplish this whole process effectively on the transputer network, we apply a pipeline based algorithm. However, the previously split image data blocks are not processed in direct pipeline, but the separated shiftings are carried out parallel on neighborhood nodes. According to the 24 significant location of a 5x5(max) operator, 24 nodes can process the shifting steps. However, this would cause a number of idling on the nodes, as no shifting process is necessary when the real size of the operators is smaller than 5x5. This problem can be avoided by allocating only the necessary number of processors to carry out the shiftings on a given data block. The input data loading and output data collection are supervised by the main transputer, and data communication tasks are executed on each subnode for data getting and passing. The outline of the calculation is illustrated in Fig. 1. The processing time ratio versus pipeline stages is drawn in Fig. 2. Pipeline stage 1/24 means that the processing is carried out sequentially on one processor. Pipeline stage 1 depicts the processing time ratio in the case when the twenty five shiftings and the minimum and maximum finding steps are carried out parallel on twenty four transputer nodes for only one operator at a time and the other eight nodes are idling. The further pipeline stages (from 4 to 32) show the processing time ratio in the cases when the transputer nodes are allocated dynamically to carry out the morphological operation steps without leaving nodes idling. In the case of 4 pipeline stages each allocated processor block has to execute eight shifting steps. While in the case of 32 pipeline stages each



a) input infrared image



a) extracted vessel shapes

Fig. 3. Blood vessel shapes on a mail breast

processor is working on a different operator in the operator sequence that contains only one significant position.

The selection and manipulation processes are accomplished in sequence on the main transputer node. The manipulation steps, such as the crossovers and mutations are carried out as concurrent processes on the individuals and individual pairs.

	Objects		
generation	0-10	11-50	51-100
20	69.1	322.4	713
50	161.2	856.3	1703.6
100	325.3	1697.2	3315.5

Fig. 4. Processing time vs. number of generations and number of objects

4. APPLICATION RESULTS

The method is applied to the shape extraction of blood vessels located in the corium and subcutis. Input images are taken by CCD camera from various skin regions, by applying infrared filtering for the near infrared (700-1000nm) wavelength band. As there is a sharp peak in the infrared absorption spectrum for water (980nm) in this wavelength band, we can obtain pictures with darker, light-absorbed regions contributed to blood vessels by detecting the light beam reflected from the skin surface. However, these images have a fairly low contrast as this wavelength band is near the limit, that is detectable by a common CCD camera. These pictures are sometimes noisy due to hardware problems.

An example application on a mail breast is illustrated in Fig. 3. The image size is 512x512 pixels in this case. On picture a., the input infrared image shows the infrared filtered image taken by CCD camera. The extracted blood vessel areas appear as dark regions superimposed on the input image on picture b. For this application a population of 50 individuals with a maximum length of 20 structuring elements is applied. The probability parameter chosen for crossover is set to 0.25. Mutations are accomplished with a relatively low probability that is set to 0.03. The average processing time required to carry out the method on a 512x512 size image containing 11-50 blood vessel regions is less than 850 ms. The processing time that is necessary to carry out the processes on the network varies upon the number of processing loops that have to be calculated. Fig. 4. shows the average processing time necessary to carry out the computation on different number of generations. As it is shown in this figure, this processing time increases significantly if the number of generations exceeds 100. For images containing a large number of vessel shapes of different sizes or unbalanced geometrical distribution, this processing time can be relatively high due to the frequent data reloading resulted in a communication overhead on the network. The parallel processes, implemented on the transputer system are written in occam 2, while the user and controlling interface is written in C on the host Sun workstation using the UNIX multithread and interprocess communication features.

5. CONCLUSION

In this paper, an evolutionary approach using gray-scale morphological sequences for object shape detection is introduced. Unlike the usual shape extraction techniques, in our approach no constraints are used for background and contrast. Also no a priori knowledge of the object shape is necessary. This method can perform well even in the case of noisy pictures. It is not guaranteed, that the optimal solution is always found, but the evolutionary approach provides global and directed search on the space of possible solutions to find a nearly good one. The entire space of morphological operators up to a given size, can be attained by carrying out crossover and mutation processes that can be very large and it gives a real benefit to the method. It is very important to find an appropriate data structure for encoding the individuals not only to ensure an effective computation but mostly for the proper representation of the connectivity constraints. By this method, we introduced a promising algorithm that may also be applied to shape detection on a wide range of images. However, the determination of really effective evaluation and representation structures based on an exact description of the solutions requires severe theoretical research.

6. REFERENCES

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