

HIERACHIC TEXTURE CLASSIFICATION USING MORPHOLOGICAL GRADIENTS AND GENETIC ALGORITHMS

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Abstract

A novel method for adaptively selecting texture features is presented. We use genetic algorithm to search for an optimal set of structuring elements which provides the best discrimination of textures. Moreover, a tree structure containing the selected set of structuring elements has been set up for classification. Experiments show that by the proposed method can achieve high classification accuracy by employing only a few structuring elements.

1. Introduction

Texture analysis is an important component of image processing. The first problem encountered in texture analysis is the extraction of features from texture image. Numerous approaches have been proposed for characterizing textures and extracting features. Among them, those based on mathematical morphology are potentially powerful. For gray scale texture analysis, Peleg et al. use gray scale morphology to measure the changes in image area of different resolutions [1]. However, it is time consuming. Linnett and Richardson [2] propose a modified method to improve the complexity by using a fixed number of variant directional structuring elements. Although one resolution alone is sufficient in their method, fixed features may not satisfy the real case of large set of textures for the lack of flexibility. Therefore, if a set of high-efficient structuring elements can be dynamically generated according to the characteristics of input texture images, only suitable and sufficient structuring elements are needed to provide best texture discrimination in the texture analysis. Thus, it is desirable to propose methods for searching the optimal set of structuring elements.

In this paper, a novel methodology is introduced for texture classification by combining a morphological notion called *Morphology Gradients* [3] with a machine learning technique termed *Genetic Algorithms* (GAs). GAs are used to evolve high-performance set of structuring elements which provide the best discrimination of textures. Once optimal structuring elements are selected by GAs, we extract features by these structuring elements and maintain a data structure, a binary decision tree, to contain these structuring elements. Then, hierachic classification is performed by traversing the binary decision tree. Experimental results show that only a few

efficient structuring elements are needed to achieve high accuracy classification rate.

2. Morphological processing

Mathematics morphology [4,5] has been widely used for biomedical and electron microscopy image analysis. Morphological image processing can be employed for many purposes, including preprocessing, edge detection, segmentation, and texture classification.

Most morphological operations can be defined in terms of two types of basic operators, *erosions* and *dilations*. Let f be a gray scale image and b a structuring element. The erosion of the gray scale image f by structuring element b , written as $f \ominus b$, is defined as

$$(f \ominus b)(x, y) = \min_{(i, j)} \{f(x+i, y+j) - b(i, j)\}$$

The dilation of the gray scale image f by structuring element b , written as $f \oplus b$, is defined as

$$(f \oplus b)(x, y) = \max_{(i, j)} \{f(x+i, y+j) + b(i, j)\}$$

Surface area of an image is one of the important features in texture analysis and has its origin in fractal methodology. The area of an image f is calculated by measuring the volume of the blanket around the image and can be defined as

$$V = \sum_{(x, y)} (f \oplus b)(x, y) - (f \ominus b)(x, y)$$

Where $(f \oplus b) - (f \ominus b)$ is called *morphological gradient* and is widely used in edge detection, edge enhancement, and image segmentation. One thing should be noted is that the value of V is sensitive to the shape of the employed structuring element. In this paper, we will use surface areas as features of textures in texture classification.

3. Genetic Algorithms

Genetic algorithms [6] are powerful optimization and adaptation techniques for optimization problems. They are efficient systematically searching methods which can reduce the searching time for many problems with large search space. At each iteration, known as a generation, each individual is evaluated and recombined with others on the basis of its fitness.

A simple genetic algorithm in many practical problems is composed of three operators : reproduction, crossover, and mutation.

Reproduction is a process in which individual strings are copied (passed) to a next generation according

to their fitness function for some particular purpose. In other words, strings with higher fitness have higher probabilities of contributing one or more offsprings in the next generation. This operation, of course, is an artificial version of natural selection. Crossover operator crosses over pairs of individuals which are represented by their genes in a certain way so that properties of both individuals are combined. For example, a one-point crossover operator operates by selecting a random location in the gene string of the parents (crossover point) and concatenating the initial segments of one parent with the final segment of the other parent to create a new child. The second child is simultaneously generated using the remaining segments of the two parents. The mutation operator randomly changes the value of one or few chromosomes in the gene of each individual.

The method proposed in this paper uses genetic algorithms to search for the optimal (or near optimal) structure elements. Each structuring element is represented as bits of string. Chromosomes correspond to structuring element pixels.

4. Hierarchic Texture Classification

We propose a strategy in the context of supervised classification. This procedure is performed with two stages: the learning stage and the classification stage.

During the learning stage, we use genetic algorithms to dynamically select optimal structuring elements. At the same time, a binary decision tree based on the method of branch and bound is maintained. Then we use the feature extracted by the optimal structuring element to divide current class of textures into two subclasses of textures. The same process repeats in the next time except that the training set is replaced by subclass of textures separated in the previous step.

For the classification stage, texture classification is performed by traversing the binary decision tree constructed in the learning stage.

4.1. Learning and constructing of decision tree

The representation of a gene as a string of chromosomes is presented. We code a binary structuring element as the string form where rows of the two-dimension structuring element are concatenated into a string and each bit corresponds to a chromosome.

The fitness of each individual is computed for each generation in order to evolve more efficient individuals in the next generations. In this particular application, the optimal structuring element with the best fitness will provide the best discrimination between the textures in the class.

Assume that there are M textures in the class. Let I_j be the jth textured image, S_i be the ith structuring element, and

$$X'_j(S_i) = \sum_{(x,y)} \{(I_j \oplus S_i)(x,y) - (I_j \ominus S_i)(x,y)\}$$

be the feature of the jth texture, that is, the surface area of

the jth texture image. Reorder X'_j 's as a monotone increasing order and relabel them as $Y'_1 \leq Y'_2 \leq \dots \leq Y'_M$. Since larger gap will provide better tolerance against distortion, as large as possible gaps between consecutive Y'_j 's are desired to divide M textures into two subclasses. Therefore, the fitness function for structuring element S_i is defined as

$$fit(S_i) = \max(Y'_j - Y'_{j-1}) \quad j=2,3,\dots,M$$

which is the largest gap among all gaps.

The steps of procedure for searching the optimal structuring elements are described as follows.

Procedure 1:

1. Input a class of M textures.
2. Create initial generation of N genes representing N structuring elements.
3. Repeat
 - <1> for $i=1,\dots,N$ (all structuring elements)
 - (a) for $j=1,\dots,M$ (all textured images)

$$X'_j = \sum_{(x,y)} \{(I_j \oplus S_i)(x,y) - (I_j \ominus S_i)(x,y)\}$$

(b) reorder X'_j 's as Y'_j 's (where $Y'_1 \leq Y'_2 \leq \dots \leq Y'_M$)

(c) $fit(S_i) = \max(Y'_j - Y'_{j-1}) \quad j=2,3,\dots,M$

<2> reproduction of genes.

<3> crossover of genes.

<4> mutation of genes.

4. Until satisfied.

5. Compute threshold = $(X_i + X_k) / 2$. Where (X_i, X_k) is the feature pair which makes maximal gap.

An optimal structuring element and a threshold value for current class of textures are determined by above procedure. Then the parent node is modified to contain the selected structuring element and the threshold value. And two children nodes each containing the textures numbers are newly inserted into the binary decision tree. The terminal node will contain a particular texture number.

4.2. Classification

A binary tree is traversed first at root. For every testing image the feature is computed by structuring element stored in the node and then decision is made by comparing the feature with the threshold value. When a terminal node is reached the testing image is assigned to the texture specified by the terminal node and searching terminates.

The height of the decision tree is near $\log_2 N$ (N is the number of total textures). Therefore, the average searching depth for a testing image is about $\log_2 N$. In other words, an assignment of texture will be determined by $\log_2 N$ operations. This is superior to the traditional methods with a fixed set of structuring elements.

5. Experimental results

Eight natural textures [7] showed in Fig.1 are used in our experiment. These textures have been digitized with 256×256 spatial resolution and quantified into 256 gray levels. Each image is divided into 16 non-overlapping 64×64 subimages. Among them, the first subimage is used as a training pattern, and the remaining 15 subimages of each texture, 120 subimages altogether, are taken as testing images to be classified.

Fig.2 shows the learning cycle of structuring elements for the set of eight textures in Fig.1. The binary decision tree set up in the learning stage and classification results are listed in Fig.3 and Table.1, respectively. It can be seen from Fig.2 that only average $(2 \times 2 + 3 \times 3 + 4 \times 1 + 5 \times 2) / 8 = 3.3 = \log_2 8$ features are computed for a given testing image before reaching the terminal node. Table 1 shows the classification accuracy rate which is about 98%.

6. Conclusion

A novel method for texture classification based on morphological gradients and genetic algorithms has been proposed in this paper. The method uses genetic algorithm to search for the optimal set of structuring elements which provide the best discrimination of textures. A data structure, known as decision tree, containing the optimal set of structuring elements has been constructed for the purpose of classification. This data structure is dynamically set up according to the input testing textures. Experiments show that, by means of this data structure, only a small set of structuring elements is sufficient to obtain high classification accuracy.

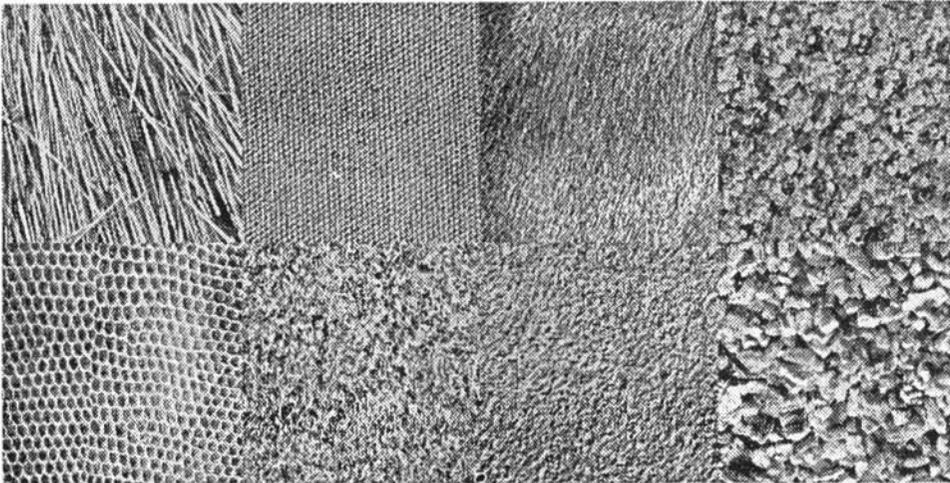


Fig.1. Eight texture images: (D93) fur, hide of unbon calf, (D28) brach sand, (D4) pressed cork, (D5) expanded mica, (D15) straw, (D77) cotton canvas, (D9) grass lawn, and (D3) reptile skin.

performance

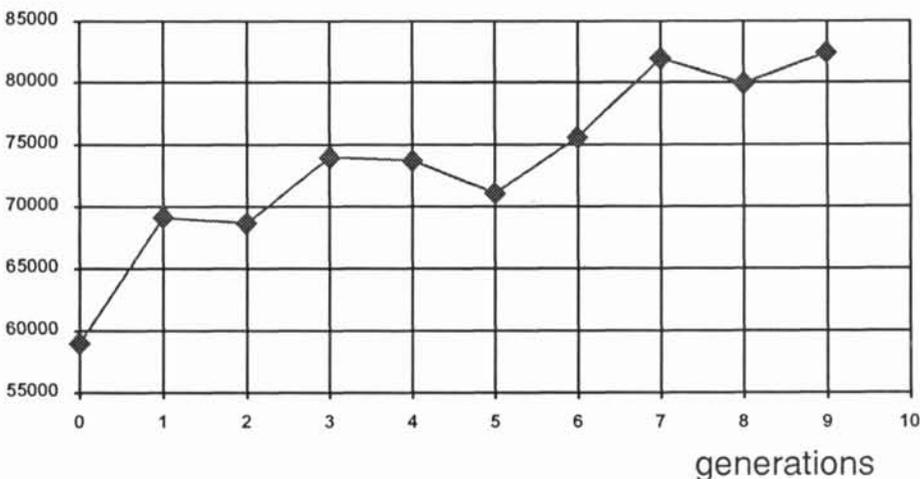


Fig.2 GAs learning cycles of structuring element for the set of textures in Fig.1.

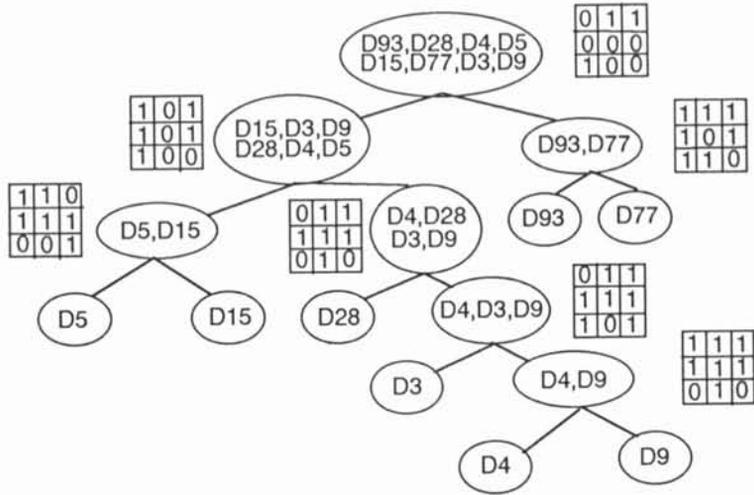


Fig. 3 Decision tree for textured image in Fig. 1. The 3×3 masks are structuring elements selected by GAs.

Table 1
Classification Results for the Texture Image in Fig. 1

texture	D93	D28	D4	D5	D15	D77	D3	D9	total correct rate (%)
D93	14	0	0	0	0	1 *	0	0	98.33
D28	1 *	14	0	0	0	0	0	0	
D4	0	0	15	0	0	0	0	0	
D5	0	0	0	15	0	0	0	0	
D15	0	0	0	0	15	0	0	0	
D77	0	0	0	0	0	15	0	0	
D3	0	0	0	0	0	0	15	0	
D9	0	0	0	0	0	0	0	15	

*: misclassification

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