

## THE DECISION OF THE OPTIMAL PARAMETERS IN MARKOV RANDOM FIELDS OF IMAGES BY GENETIC ALGORITHM

Zhaobao Zheng , Hong Zheng  
School of Information Engineering  
Wuhan Technical University of Surveying and Mapping  
129 Ruoyu Road, 430079, Wuhan, P.R.China  
[zbzheng@wtusm.edu.cn](mailto:zbzheng@wtusm.edu.cn)

Working Group WG /3

**KEY WORDS:** Genetic algorithm, Markov Random Field, Parameter optimum, Texture classification

### ABSTRACT

This paper introduces the principle of genetic algorithm and the basic method of solving Markov Random Field parameters. Focusing on the shortcoming in present methods, a new method based on genetic algorithms is proposed to solve the parameters in the Markov Random Field. The detail procedure is discussed in this paper. On the basis of the parameters solved by genetic algorithm, some experiments on classification of aerial images are given in this paper. Experiment results show that the proposed method is effective and the classification results are satisfied.

### 1 INTRODUCTION

Image texture is an important feature for image processing and analysis .The study in the past twenty years shows that Markov Random Field (MRF) is a powerful tool to describe image features. Now MRF is often used in image texture classification. This is because image features can be described quantitatively by a group of MRF parameters, and different MRF parameters represents different image textures(Zhaobao Zheng/1996, Hong Zheng/1997). So the key problem applying MRF in image texture classification is how to decide the optimal MRF parameters. A lot of scholars have been studying the problem .They attempt to configure two or three pixels around a central pixel as a group, which is called *cliques* . They think that image textures are the configurations of these *cliques*, and each *cliques* corresponds to a parameter . The value of the parameter reflects the attribute of the *cliques* corresponding to the parameter .The larger the value is , the more the *cliques* a image texture contains. If the value is negative ,it means the *cliques* will restrain image textures. Virtually ,the decision of the optimal parameters is to decide the optimal configuration of *cliques* . For a 256 level gray image , the number of configures may be  $256^3$  (two-order MRF).The number is so large that it is difficult to find the optimal configuration .In addition , the textures of aerial images are too complex to be described by simple *cliques*. According to our study ,they should be described by five-order MRF. In the case, the number of neighbors is 24,and each neighbor pixel corresponds to a parameter whose value reflects the relation between the neighbor and its central pixel. The relation can be expressed as a relation function about central pixels and their neighbors. Theoretically, parameter can be computed from the function by the least square method. But , for a 256 level gray image ,because the gray values corresponding to two or three parameters in the function may be same or close , the function may have no solution . In order to solve the problem ,this paper presents to decide optimal neighbors by genetic algorithm . Genetic algorithm is a global optimal algorithm . It has robust, fast and parallel features .This paper regards the sum of square of residuals as fitting function ,and discusses the detail produce to solve MRF parameters by genetic algorithm ,which includes encoding, decoding, crossover and mutation etc.. Experiment results are given to show the classification effectiveness of the method proposed in the paper .

### 2 THE DECISION OF THE OPTIMAL PARAMETERS IN MRF BY GENETIC ALGORITHMS

#### 2.1 Overview of Genetic Algorithm

The genetic algorithm proposed by John Holland has been recently exploited in pattern recognition problems involving optimization processes that provide a suitable solution in handling uncertainty in pattern analysis(D.E. Goldberg/1989). The genetic algorithm (GA) is an adaptive procedure that searches for good solutions by using a collection of search

points known as a population in order to maximize some desirable criterion. Also, the GA, as a stochastic random search technique, is known to use the accumulating information to prune the search space, while a purely random search ignores information about the environment.

The GA is an iterative procedure with a parallel test-and-go technique, which maintains a finite set of representations for solving a given problem. During each iteration step, known as generation, each individual is evaluated and recombined with others on the basis of its overall quality or fitness. Each individual is represented as a chromosome encoded as a string of genes which may take one of several values or alleles.

Some recent attempts in applying the genetic algorithms for machine vision problems (B.Bhanu/1989, G.Roth and M.D.Levine/1991) such as image segmentation, primitive extraction, scene recognition and image interpretation are reported in the literature. Bhanu, Lee and Ming proposed a learning technique for the image segmentation using the GA. The algorithm allows the segmentation process to adapt to image characteristics affected by the variable environmental conditions such as time of day, clouds, rain, etc. Also in handling uncertainty in pattern analysis, Pal reported a necessity of a fuzzy fitness function.

Recently, research of GA has focused on three operators such as reproduction, crossover and mutation. Reproduction is a process in which individual strings are copied according to their objective function as some measure of goodness we want to maximize. The crossover involves exchanging elements from mating of two parent chromosomes to create one or more child chromosomes. The crossover is implemented by randomly choosing a point in the string called the crossover point and exchanging the segments. There are various crossover mechanisms that have been developed to be efficiently applied to applications, for instance, cycle crossover, order crossover, position based crossover, partially mapped crossover and so on. The mutation process creates new individuals by modifying one or more bit strings. The operator increases the variability of the population and prevents premature convergence to a poor local minimum. One of the interesting aspects in designing a genetic algorithm is to invent operators that construct the new potential solutions.

In this paper we apply the GA to search optimal parameters of the MRF for image classification. To do so, we design the crossover and the mutation mechanism for solving MRF parameters, as well as an encoding scheme of the chromosome for representing the mask. However, the basic procedure of GA is based on the Simple Genetic Algorithm (SGA). We describe the detailed mechanism in next sections.

## 2.2 The Genetic Algorithm for the Decision of the Optimal Parameters in MRF

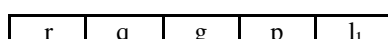
MRF is an important statistic model to analyze textures. It regards texture as the reflection of statistic features of pixel gray value. In the MRF, each pixel is named a texture primitive. Different statistic regulations of texture primitives reflects different texture features. These statistic regulations can be described by MRF parameters whose values reflect the relation between the neighbor and its central pixel (Zhaobao Zheng /1997). The relation can be expressed as (Kashyep R.L /1981):

$$y(s) = \sum_{r \in h} b_r \cdot y(s+r) + n(s) \quad (1)$$

Where  $y(s)$  is the gray of a central pixel,  $h$  is the set of neighbors of the central pixel;  $y(s+r)$  is the gray of a neighbor pixel of  $y(s)$ ;  $r$  is the distance radius;  $b_r$  is a MRF parameter;  $n(s)$  is Gaussian noise or called residuals;  $s \in \mathcal{U}$ ,  $\mathcal{U}$  is the size of a textured image, and the average of  $y(s)$  is zero. Eq.1 can be transformed as following error equation:

$$-n(s) = \sum_{r \in h} b_r \cdot y(s+r) - y(s) \quad (2)$$

For a five-order MRF which is shown in Fig.1, there are 24 neighbor pixels around a center pixel. As a result, there are 24 unknown parameters in Eq.2.



|                |                |                |                |                |
|----------------|----------------|----------------|----------------|----------------|
| f              | v              | u              | w <sub>1</sub> | s              |
| h              | t              | x              | t <sub>1</sub> | h <sub>1</sub> |
| s <sub>1</sub> | w              | u <sub>1</sub> | v <sub>1</sub> | f <sub>1</sub> |
| l              | p <sub>1</sub> | g <sub>1</sub> | q <sub>1</sub> | r <sub>1</sub> |

Figure 1. The structure of five-order MRF

In this section, we will discuss how to apply genetic algorithm in solving above 24 parameters. It includes following aspects.

**2.2.1 Encoding Scheme of Chromosome.** Now we define a set of individuals in a population generated during *t* generation cycles.  $P(t)=\{I_k|k=1,2,\dots,m\}$ , where *m* is the number of individuals or the population size. The size affects both the ultimate performance and the efficiency of GA. Each individual is generated by some encoded form known as a *chromosome*.

For a five-order MRF, the error equation is:

$$\begin{aligned}
 -n(x) = & b_1 r + b_2 q + b_3 g + b_4 p + b_5 l_1 + b_6 f + b_7 v \\
 & + b_8 u + b_9 w_1 + b_{10} s + b_{11} h + b_{12} t + b_{13} t_1 + b_{14} h_1 \\
 & + b_{15} s_1 + b_{16} w + b_{17} u_1 + b_{18} v_1 + b_{19} f_1 + b_{20} l + b_{21} p_1 \\
 & + b_{22} g_1 + b_{23} q_1 + b_{24} r_1 - x
 \end{aligned}
 \tag{3}$$

Total 24 parameters( $b_1 \sim b_{24}$ ) are encoded as a chromosome. Each parameter is represented by a 16-bit binary string. Fig. 2 illustrates the chromosome structures.

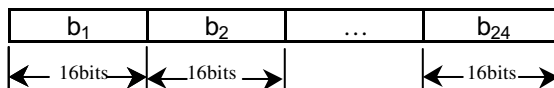


Figure 2. A five-order MRF chromosome structure

The range of MRF parameters is defined in [-6.0,6.0]. For a 16-bit binary string corresponding to a parameter, the decoding equation is:

$$b_i = -6.0 + \frac{12.0 \cdot \sum_{j=0}^{15} B_{ij} \cdot 2^j}{2^{16}} \quad i = ,1,2,\dots, 24
 \tag{4}$$

Where  $B_{ij}$  is a bit value (0 or 1) of parameter  $b_i$ .

**2.2.2 Fitness Function.** Based on Eq.3, the fitness function is defined as:

$$f = \sum_{i=1}^N \sum_{j=1}^N v^2(x_{ij})
 \tag{5}$$

Where *M* is the width of the image, *N* is the height of the image.  $v(x_{ij})$  is the value of the error function at pixel  $x_{ij}$ .

**2.2.3 Crossover operator.** The crossover is an important operator in GA. It is first begun by selecting two chromosomes of parents ( $P_1$  and  $P_2$ ) randomly in a population. The selection is randomly determined by the Roulette Wheel slot whose size is proportional to the fitness. Also, the crossover of  $P_1$  and  $P_2$  is determined by a probability of the crossover rate  $P_{crossover}$ . Here, the MRF parameters in a parent need to do crossover operation with the same parameter from the other parent. As a result, 24 crossover points will be generated. Each crossover point is selected by

random from 0~15. Then the elements at the crossover points in the  $P_1$  directly exchange with the same elements from  $P_2$  and inherits two children. The detailed algorithm of the crossover mechanism is shown in Fig.3.

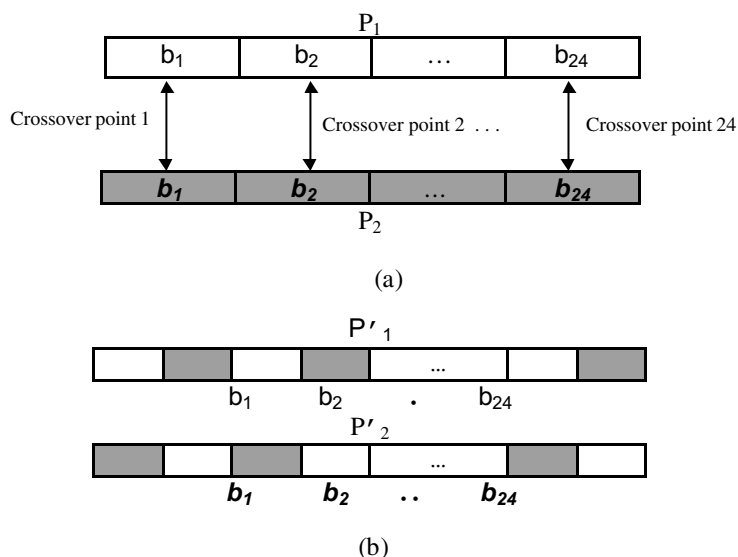


Fig.3 An example of the crossover

(a) Two parent chromosomes  $P_1$ ,  $P_2$

(b) Two child chromosomes  $P'_1$  and  $P'_2$  generated by crossover operation between  $P_1$  and  $P_2$

**2.2.4 Mutation Operator.** Mutation is a secondary search operator which increases the variability of the population and the ability of exploring the optimal solution. The mutation operator creates new individuals by changing one or more of the gene values in the chromosome with a probability equal to the mutation rate  $P_{mutation}$ . The operator entails the two decision phases. The first is to randomly select a chromosome from the population. The second is to randomly select a bit from the chromosome as the mutation point and take its reverse value as its value, e.g. 0  $\rightarrow$  1, 1  $\rightarrow$  0.

**2.2.5 The Procedure of Deciding MRF Optimal Parameters Based on Genetic Algorithm.** The procedure of deciding MRF optimal parameters based on genetic algorithms is given below, where  $P(t)$  is a population of candidate parameters at generation  $t$ .

```

t=0;
initialize P(t)
evaluate P(t)
while not (termination condition)
  begin
    t=t+1;
    reproduce P(t) from P(t-1)
    recombine P(t) by crossover and mutation operator
    evaluate P(t)
  end;
end while

```

### 3 TEXTURE CLASSIFICATION BASED ON MRF PARAMETERS

Traditional texture classification methods based on MRF parameters regard the value of MRF parameters as the main features for classification. But during our study, we discover that the signs of parameters of different textures are not all the same. In other words, the signs of parameters of the same textures must be the same. If the signs of parameters of two textures are different, they must not be the same texture. So we presents following procedure of texture classification:

- (1) According to texture samples, standard MRF parameters of different texture classes are acquired by genetic algorithms.
- (2) To solve MRF parameters of a unknown texture image by GA.

- (3) If the signs of the MRF parameters of the unknown texture image solved by GA are only the same as the signs of the parameters of some texture sample, the unknown texture image is the same texture class as the texture sample. If the signs are the same as the signs of the parameters of two or above texture samples., the least distance method is used to classification.

#### 4 EXPERIMENTAL RESULTS

In order to test the ability of texture classification based on MRF parameters solved by GA, we do classification experiments on seven classes of textures. These textures include 23 residential area textures, 12 rice field textures , 15 hill textures , 35 river textures , 11 valley textures, 48 frutex textures, 20 mountain region textures. Table 1 lists the signs of MRF parameters of different textures. From Table 1, we can see that the signs of MRF parameters of different textures are not all the same. It shows that the signs of MRF parameters can be regarded as an important texture feature.

| Parameter<br>Texture | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|----------------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
|                      | - | + | - | + | - | + | + | - | + | +  | -  | +  | -  | -  | +  | -  | +  | +  | -  | -  | +  | -  | -  | +  |
|                      | - | + | - | + | + | + | - | + | - | -  | -  | +  | -  | +  | +  | -  | +  | +  | -  | -  | +  | -  | +  | -  |
|                      | - | + | - | + | - | + | - | + | - | +  | +  | -  | -  | +  | -  | +  | +  | -  | +  | +  | -  | -  | +  | -  |
|                      | - | + | - | + | - | + | - | + | - | +  | -  | +  | +  | -  | +  | -  | +  | -  | -  | -  | +  | -  | +  | +  |
|                      | - | + | - | - | + | + | - | + | - | +  | -  | +  | +  | -  | +  | -  | +  | -  | +  | +  | -  | +  | -  | +  |
|                      | + | - | + | + | - | + | - | - | + | -  | -  | +  | +  | +  | -  | +  | -  | +  | -  | +  | -  | +  | -  | +  |
|                      | - | + | - | + | - | + | - | + | - | +  | -  | +  | +  | -  | -  | +  | +  | -  | -  | +  | -  | -  | +  | +  |

Table 1. The signs of MRF parameters of different textures

: residential area texture ,: rice field texture ,: hill texture, : river texture,: valley texture, : frutex texture, : mountain region texture

| Method                  | Recognition rate |            |       |       |        |        |                 |
|-------------------------|------------------|------------|-------|-------|--------|--------|-----------------|
|                         | Residential area | Rice field | Hill  | River | Valley | Frutex | Mountain region |
| The least square method | 61.5%            | 78.9%      | 88.2% | 75%   | 64.2%  | 85.3%  | 59%             |
| Fractal method          | 92.2%            | 78.9%      | 88.2% | 90%   | 92.8%  | 95%    | 90.9%           |
| Author method           | 92.2%            | 89.6%      | 97.4% | 83.8% | 94.6%  | 95.9%  | 92.2%           |

Table 2. The results of classification with three methods

According to the classification method proposed in section 3 , we classified above 164 textures. In addition , in order to compare the classification ability of different classification methods, we also classified above 164 textures with the least square method based on MRF parameters and fractal method respectively. Table 2 lists the results of classification with three methods.

From Table 2 , we can see that the texture recognition rate of the method proposed in this paper is higher than the rate of other two methods except river texture. It shows that it is much effective to apply MRF parameters decided by genetic algorithm in texture classification.

## 5 CONCLUSION

In this paper we have shown how to apply genetic algorithm in deciding MRF parameters and use these parameters to classify texture images. Experiment results show the effectiveness and practicality to apply genetic algorithm in texture classification. Further work needs to be carried out in combining the MRF parameters decided by GA with other texture features to improve the recognition rate further.

## ACKNOWLEDGEMENTS

The authors would like to thank the project(No.49871067) of the Nation Nature Science Foundation for supporting.

## REFERENCES

B.Bhanu, S.Lee and J.Ming, 1989. Adaptive image segmentation using a genetic algorithm, Image Understanding Workshop,pp.1043-1055.

D.E. Goldberg, 1989. Genetic Algorithm in Search, Optimization and Machining Learning, Addison-Wesley Co.,Massachussets .

G.Roth and M.D.Levine,1991. A genetic algorithm for primitive extraction, Proc. 4th Intl Conf. Genetic Algorithm, San Diego.,pp.487-497.

Hong Zheng and Zhaobao Zheng, 1997. The knowledge acquirement for image understanding based on MRF, Journal of Wuhan Technical University of Surveying and Mapping, Vol.22,No.4,pp314~317.

Kashhyep R.L ,Chellappa R. And Ahuja N., 1981. Decision rules for choice of neighbors in random field models of images, Computer Graphics and Image Processing, Vol.15,pp.301~308.

Zhaobao Zheng and Guilan Huang,1996. The least square method for aerial image texture classification and its problem analysis, Journal of Surveying and Mapping, Vol.25,No.2, pp.121~126.

Zhaobao Zheng and Yueqing Zhou, 1997. On texture and its description of aerial image texture, Journal of Surveying and Mapping, Vol.26,No.3, pp.222~227.