Set of texture similarity measures

Abdurrahman Çarkacıoğlu[a], and Fatoş T. Yarman-Vural[b]

[a] Capital Markets Board of Turkey
[b] Middle East Technical University, Dept. of Computer Engineering
TÜBİTAK-BİLTEN Information Technologies and Electronics Research Institute

ABSTRACT

This paper deals with a class of textures which can be represented by Markov Random Fields (MRF) model. It is well known that by changing the MRF parameters, extremely wide group of textures can be generated. However, it is not easy to model and classify a textured image, since there is no clear-cut mathematical definition of texture. Although, many classification methods exist in the literature, the success of the results heavily depends on the data type. Thus, appropriate measures which give visually meaningful representation of texture are highly desirable.

In this study a new set of texture measures, namely, *Mean Clique Length (MCL)* and *Clique Standard Deviation (CSD)* is introduced. These measures are defined employing new concepts which agrees with the human visual system. The simulation experiments are performed on binary MRF texture alphabet to quantify the data by the MCL and CSD measures. Experimental results indicate that the introduced measures identify the visually similar textures much better than the mathematical distance measures.

Keywords: Markov Random Field, texture, texture similarity, clique, feature, similarity measure

1. INTRODUCTION

Texture plays an important role in many image processing and computer graphics problems. It provides information on the depth and orientation of an object. Understanding texture is, also, an essential part of understanding the human visual system. Unfortunately, there is no universally accepted definition for texture. Loosely speaking, texture can be defined as a stochastic, possibly periodic, two dimensional image field. In recent computer vision literature there has been an increasing interest in the use of statistical techniques for modeling and processing the textured image. Some of this work has been directed towards the application of Markov Random Fields (MRF) in texture modeling, classification and restoration of noisy and textured images.

Texture generation using the MRF model is a classical problem. Using different set of parameters, it is possible to generate extremely wide class of textures. However, it is not easy to generate a desired form of texture, since the relationship between the model parameters and certain features of texture is not a linear one. Although, interest in MRF models for tackling image processing problems can be traced back to the work of Abend[4], only recently have appropriate mathematical tools for exploitation of the full power of the MRF in image processing been developed. The reports by Cross and Jain[6], Geman and Geman[3], Cohen and Cooper[10], and by Derin and Elliott[5] all make use of Gibbs Distribution for characterizing the MRF.

In this study, a set of measures is introduced to quantify the similarity of textures which can be modeled by Markov Random Fields (MRF). First, a brief explanation of MRF model is given in Section 2. Texture realization problem is addressed in Section 3. Then, based on the theoretical studies and various observations, a set of texture measures are defined in Section 4. In Section 5, simulation experiments are performed to determine the relation between the data type, model parameters and the texture measures defined in Section 4. Section 6, concludes the paper by discussing the proposed texture measures and commenting on the directions of the feature research.

Further author information -
A.Ç. : Email: carkaci@ceng.metu.edu.tr
F.T.Y.V : Email: vural@ceng.metu.edu.tr; WWW: http://www.ceng.metu.edu.tr/~vural; Telephone: + 90 312 2105595

2. MARKOV RANDOM FIELDS (MRF) FOR TEXTURE MODELING

Consider the random field defined over a finite lattice of points (i, j) :

$$L = \{(i,j): 1<i<N_1,\ 1<j<N_2\}. \qquad (1)$$

A collection of subsets of L described as,

$$\eta = \{\eta_{ij} : (i,j) \in L,\ L \supset \eta_{ij}\}\ , \qquad (2)$$

is a neighborhood system on L iff η_{ij}, the neighborhood of pixel (i,j), is such that

(a) $(i,j) \notin \eta_{ij}$,
(b) $(k,l) \in \eta_{ij}$, for any $(i,j) \in \eta_{kl}$.

A random field X = { X_{ij} }, defined over the lattice L, is a Markov Random Field (MRF) with respect to the neighborhood system η, iff the distribution of X is of the form,

$$P(X=x) \geq 0\ ,\ \forall x \ \text{ and} \qquad (3)$$

$$P(X_{ij} = x_{ij} \mid \{ X_{kl} = x_{kl}\ ,\ (k,l) \in L,\ (k,l) \neq (i,j) \}\ ) =$$

$$P(X_{ij} = x_{ij} \mid \{ X_{kl} = x_{kl}\ ,\ (k,l) \in \eta_{ij} \}\ )\ , \text{ for all } (i,j) \in L. \qquad (4)$$

The Neighborhood structure for η^1(first order) and η^2(second order, eight neighbor) are shown in Fig. 1, where $\{ u_i \}^4_{i=1}$ indicates the first order neighborhood, whereas $\{ v_i \}^4_{i=1}$ indicates the additional neighbors required for the extension to the second order neighborhood.

v1	u2	v2
u1	x_{ij}	u3
v4	u4	v3

Figure 1. Eight neighbors of x_{ij}.

In this study, based on the above definition, the following binary Auto-Logistic MRF model is utilized[1]:

$$P(X = x_{ij} \mid \{u_k\}\ ,\ \{v_k\}\ ) = \frac{\exp(x_{ij}[\beta_0+\beta_1(u_2+ u_4)+ \beta_2(u_1+ u_3)+ \beta_3(v_2+ v_4)+ \beta_4(v_1+ v_3)])}{1+ \exp(\beta_0+\beta_1(u_2+ u_4)+ \beta_2(u_1+ u_3)+ \beta_3(v_2+ v_4)+ \beta_4(v_1+ v_3))} \qquad (5)$$

where x_{ij} is the value of $(i,j)^{th}$ element of the lattice L, $\{ \beta_i \}^4_{i=1}$ are the second order model parameters, $\{ u_i \}^4_{i=1}$ and $\{ v_i \}^4_{i=1}$ indicates the values at second order neighborhood of x_{ij} .

The above theoretical background is used to generate textures and estimate the model parameters. The reader is referred to [1], [2], [3], [6] for a more detailed description of Markov Random Field texture models.

3. TEXTURE GENERATION

Texture realization problem using the MRF model is addressed as a stochastic relaxation problem. In Physics, there is a well known simple algorithm, called, Metropolis algorithm, which provides an efficient simulation of a collection of atoms in equilibrium at a given temperature. This algorithm has been applied to texture generation problem by Cross and Jain [6]. In this study, the following slightly modified version of the Metropolis algorithm is used for generating the probability density function P(X) of MRF Model:

```
WHILE NOT STABLE DO
      BEGIN
          CHOOSE SITE (i, j);
          R := P(Y) / P(X);
          IF R >= 1
                    THEN CHANGE THE VALUE AT X(i, j)
                    ELSE
                              BEGIN
                                        U := UNIFORM RANDOM ON [ 0,1 ]
                                        IF R > U
                                                  THEN CHANGE THE VALUE AT X(i, j)
                                                  ELSE RETAIN X
                              END
          END;
```

The above algorithm chooses a pixel at random. If the change will take the system to a more probable (lower energy) configuration, its value is updated. If the new configuration is less probable, than the change will or will not take place, depending on the comparison of the ratio of the probabilities of the new and old configurations with a random number uniform on [0,1]. The randomization is necessary to ensure that the system does not get stuck in a locally high probability configuration. The ratio of the probabilities of the new and old configurations are calculated easily due to the Gibbs Distribution formulation without actually determining the probabilities, which would be extremely difficult. The realization Y is obtained from the realization X by changing the value at X(i,j), iteratively.

4. SET OF MEASURES FOR TEXTURE SIMILARITY

Because of its complexity and tremendous amount of variations, there is no clear-cut mathematical definition of texture. Therefore, a measure of texture which gives an idea about the data type is highly desirable. This measure would be very useful to give a quantitative idea about the texture similarity among the textures, in texture classification problem.

In the following, behind a series of definitions, a new set of texture measures is introduced. First, a simple tool for measuring various properties of texture, called base clique is defined. For this purpose, the general concept of clique[11] and neighborhood is utilized.

Definition 1: Base Clique: Given a seed pixel (i,j) in a neighborhood system η , the *base clique* of (L, η) denoted by a pair of pixels $\mathbf{B_p(ij,kl)}$ where p = 1..P , is a subset of the Lattice L such that

(a) $(i,j) \neq (k,l)$, $ij \in \eta_{kl}$ and,
(b) Pixels (i,j) and (k,l) satisfies $| x_{ij} - x_{kl} | < \varepsilon$, for a given $\varepsilon > 0$,

where P indicates the number of distinct base cliques. Fig. 2.a and 2.b indicate the base clique representation and the corresponding base cliques for second order neighborhood system η^2, respectively. For this case P=8.

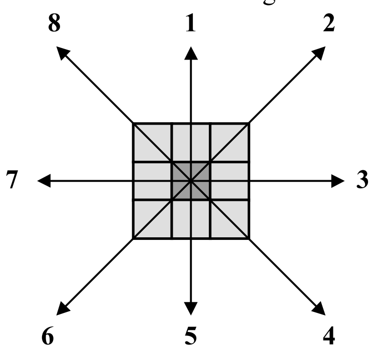

Figure 2.a. Base Clique Representation. Shaded pixel is taken as seed pixel

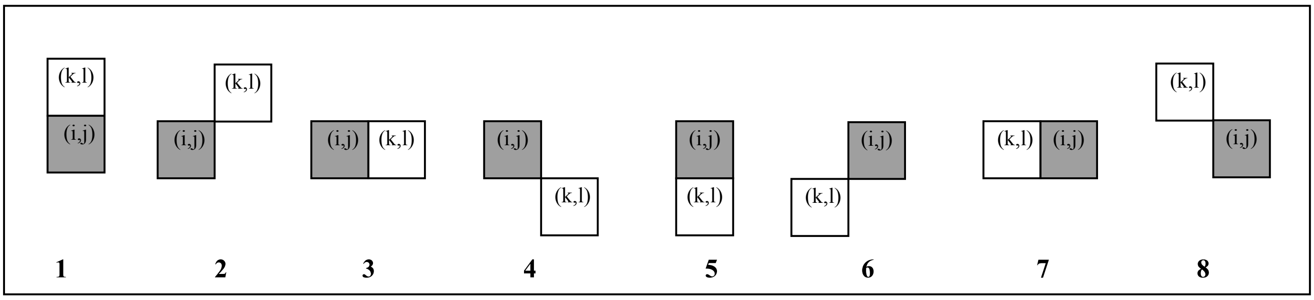

Figure 2.b. η^2 neighborhood systems and its base cliques B_P , P = 1,2..8.

Definition 2: Base Clique Chain: Given pixel (i,j) as a seed, the *base clique chain* $\mathbf{C_P(ij)}$ is the connected chain of pixels with the same base clique ,

$$\forall\ p, \quad C_p(ij) = \{ B_p(ij,kl) \cup B_p(kl,mn) \cup B_p(mn,..) \cup .. B_p(qr,st) \} \tag{6}$$

where (qr,st) is the last connected pair of pixels, with the base clique B_p.

Definition 3 : Given (i,j) as a seed , n^{th} *Order Clique Chain* is

$$O^n_Z\ (ij\ ) = \bigcup_{k\ \varepsilon z} C_k(ij) \tag{7}$$

where z is the n-combination of the integers 1,...,P. Note that the number of n^{th} order clique chain is P!/[(P-n)! **.** n!] where P indicates the number of distinct base cliques.

For example, a *second order clique chain* is a combination of two base clique chains and defined as:

$$O^2_{pq}\ (ij) = C_p(ij) \cup C_q(ij).$$

Note that there are 28 distinct second order clique chains for a seed pixel (i,j). Figure 3 illustrates some of the second and third order clique chains.

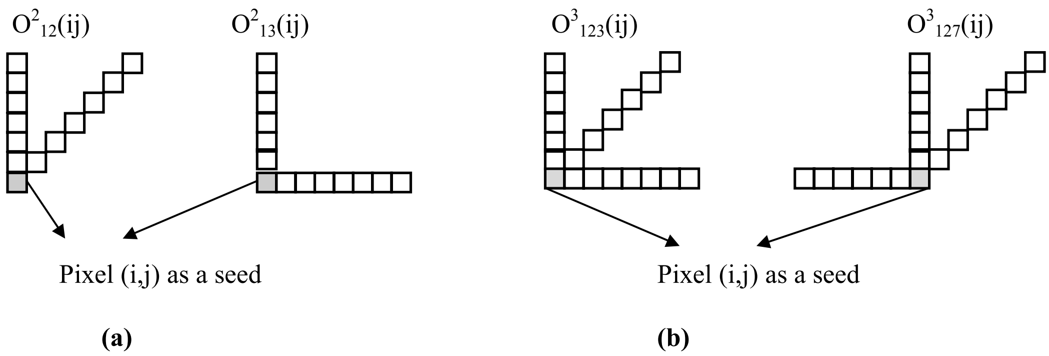

Figure 3: Some of the a) second and b) third order clique chains, respectively.

Definition 4: Given pixel (i,j) as a seed, and its base clique chain $C_p(ij)$, the **base clique length $\mathbf{L_p(ij)}$** is the number of the pixels in $\mathbf{C_p(ij)}$ **.**

In other words, the base clique length, $\mathbf{L_p(ij)}$, is the number of connected chain of pixels formed by the elements of the base clique chain , $\mathbf{C_p(ij)}$.

In a textured image, the base clique length, $\mathbf{L_p(ij)}$ of each base clique chain is computed by counting the pair of pixels as long as they belong to the same **base clique chain** set, $C_p(ij)$.

Definition 5: Given a seed pixel (i,j) and its n^{th} order clique chain $O^n{}_Z$ (ij), the **n^{th} order clique length $L^n{}_Z(ij)$,** for n > 1, is defined as follows

$$\mathbf{L_z{}^n(ij) = min \{ L_p(ij) \}}, \quad \text{where } p \in Z. \tag{8}$$

The effect of n^{th} order clique on the human visual system can be measured by considering the minimum length of the n^{th} order clique chain components , $L_p(ij)$. Suppose that, we have $O^2{}_{12}(ij)$ with base clique lengths $L_1(ij)=1$,$L_2(ij)=8$ and $O'^2{}_{12}(ij)$ with base clique lengths $L'_1(ij)=4$ and $L'_2(ij)=4$. For our visual system, $O'^2{}_{12}(ij)$ caries more second order information than $O^2{}_{12}(ij)$.

Due to the stochastic nature of the texture, $L_z{}^n(ij)$ can be considered as a random variable. Therefore, moments, especially, second order statistics of $L_z{}^n(ij)$ can give us an idea about the appearance of the texture.

Definition 6: Mean Clique Length ($MCL^n{}_Z$) is the mean value of all the clique lengths for a given n^{th} Order Clique Chain $O^n{}_Z(ij)$, found in lattice L;

$$\mathbf{MCL^n{}_Z} = E \{ \mathbf{L^n{}_Z(ij)} \}, \tag{9}$$

and **Clique Standard Deviation ($CSD^n{}_Z$)** is

$$\mathbf{CSD^n{}_Z} = [\, E \{ [\, \mathbf{L^n{}_Z(ij)} - E \{\mathbf{L^n{}_Z(ij)}\}]^2 \} \,]^{1/2}, \tag{10}$$

where E indicates the expected value operator. Notice that each base clique type is represented by a Mean Clique Length and Clique Standard Deviation.

In our numerical experiments, the Mean Clique Length and Clique Standard Deviation are approximated using the following empirical equations:

$$\mathbf{MCL^n{}_Z} \approx (1/N) \sum_{k=1}^{N} \mathbf{L^n{}_Z(ij)} ,$$

$$\mathbf{CSD^n{}_Z} \approx [\, (1/N) \sum_{k=1}^{N} [\, \mathbf{L^n{}_Z(ij) - MCL^n{}_Z} \,]^2 \,]^{1/2} ,$$

where N indicates the total number of clique chain sets in Clique type **$O^n{}_z(ij)$.** Note that the number of the MCL and CSD is the same as the number of the n^{th} order clique chains in a given texture**.**

Definition 7: For a given texture **T,** the Nx1 vector $\underline{\mathbf{M}}^n$(**T**), where the entries are the Mean Clique Lengths **$MCL^n{}_Z$** , and $\underline{\mathbf{C}}^n$(**T**) where the entries are the Clique Standard Deviation **$CSD^n{}_Z$**, for all the n^{th} order clique chains, are called the **mean clique length vector** and **clique standard deviation vector.**

$\underline{\mathbf{M}}^n$(**T**) and $\underline{\mathbf{C}}^n$(**T**) are used to represent texture **T**. At this point, any distance (Euclidean, Mahalanobis, Yule, Jakard etc.) can be used to measure the similarity between the textures by using the $\underline{\mathbf{M}}^n$(**T**) and $\underline{\mathbf{C}}^n$(**T**) vectors.

For examples, the Mean Clique Length vector of the second order clique chains for texture **T** is $\underline{\mathbf{M}}^2(T) = \{MCL^2{}_{12}, MCL^2{}_{13}, MCL^2{}_{14}, \ldots, MCL^2{}_{78}\}$. $\underline{\mathbf{M}}^2$(T) gives only a rough idea about the texture appearance. However, as the order n gets larger, the Mean Clique Length vector provides a more detailed information, with the price of increasing the dimension of $\underline{\mathbf{M}}^n$(T) . In the following, an algorithm is proposed to compute MCL and CSD for each n^{th} order clique chain.

STEP 1: FOR ALL PIXEL (I,J) ∈ L
- **A. FIND ALL OF THE BASE CLIQUE CHAINS.**
  - **IF X(I,J) IS BLACK THEN COUNT THE CONNECTED BLACK PIXELS**
  - **ELSE, COUNT THE CONNECTED WHITE PIXELS**
- **B. OBTAIN BASE CLIQUE LENGTHS**
- **C. OBTAIN N^{TH} ORDER CLIQUE LENGTHS WHERE N=2..8**

STEP 2: FOR ALL N^{TH} ORDER CLIQUE CHAIN, FIND MEAN CLIQUE LENGTHS AND CLIQUE STANDARD DEVIATION.

It is clear that $\mathbf{O^2_{15}}$, $\mathbf{O^2_{26}}$, $\mathbf{O^2_{37}}$, $\mathbf{O^2_{48}}$ clique chains are line like. For these types of clique chains, we replace the length of clique chain formulas to $L_{PQ}{}^2(ij) = L_P(ij) + L_Q(ij)$.

5. EXPERIMENTAL RESULTS

In our simulation experiments, first and second order MRF model is used for modeling binary images. Textures of size 64X64 are generated according to various settings of MRF parameters. The algorithm is implemented under C programming language.

First, textures 1-35 are generated using the Metropolis algorithm. The effects of the parameters on the texture types are investigated in two categories: β_0 and $\{\beta_1, \beta_2, \beta_3, \beta_4\}$. It is intuitively clear from Eq.(5) that β_0 controls the ratio of the white pixels to the black pixels.

Next, various effects of the parameters β_1,..., β_4 are examined:

1) Anisotrophic Effects: It is intuitively clear from Eq.(5) that while β_1 controls the vertical clustering, β_2 controls the horizontal clustering. On the other hand, β_3 and β_4 controls the left and right diagonal clustering, respectively. Anisotrophic effects can be investigated in 4 main group.

i) Vertical Textures: Textures 1 - 5
ii) Horizontal Textures: Textures 6 - 10
iii) Right Diagonal Textures: Textures 11 - 15
iv) Left Diagonal Textures : Textures 16 - 20

2) Ordered Patterns: Many of the application of the Ising model involve studying the checkerboard-like patterns obtained with negative clustering parameters. This is illustrated by Textures 21-25, where the most likely configuration is a black pixel surrounded by four white pixels or vice versa.

3) Clustering Effects : Textures 26 through 30 show clustering effect of a series of binary textures generated according to the first order model with $\beta_3 = \beta_4 = 0$. The size of the clusters increases proportional to the β_3 and β_4 parameters.

4) *Attraction-Repulsion Effects:* An attraction-repulsion process involves having low-order parameters positive, resulting in clustering, but high-order parameters negative in order to inhibit the growth of clusters. If high order parameters were also positive, large clusters would result, whereas negative high order parameters yield small clusters (Texture 31 through 35)**.**

All the β parameters of the generated textures are shown in Table 1. In the experiments, second order clique chain measures, namely , $\mathbf{MCL^2_{13}}$, $\mathbf{MCL^2_{15}}$, $\mathbf{MCL^2_{17}}$, $\mathbf{MCL^2_{24}}$, $\mathbf{MCL^2_{26}}$, $\mathbf{MCL^2_{28}}$, $\mathbf{MCL^2_{35}}$, $\mathbf{MCL^2_{37}}$, $\mathbf{MCL^2_{46}}$, $\mathbf{MCL^2_{48}}$, $\mathbf{MCL^2_{57}}$, and $\mathbf{MCL^2_{68}}$ are used**.** But, it may be necessary to use higher order clique chains for real life textures.

The Mean Clique Lengths and Clique Standard Deviations for a given texture are scaled to 1 by dividing all the Mean Clique Length and Clique Standard Deviation to the value of the maximum mean clique length and maximum clique standard deviation of the texture, respectively. This scaling provides invariancy in size and dimension of texels.

Experimental result indicates that, the maximum Mean Clique Lengths are obtained for
- anisotropic vertical textures as $\mathbf{MCL^2_{15}}$,
- anisotropic horizontal textures as $\mathbf{MCL^2_{37}}$,
- anisotropic right diagonal textures as $\mathbf{MCL^2_{48}}$,
- anisotropic left diagonal textures as $\mathbf{MCL^2_{26}}$,
- ordered patterns as $\mathbf{MCL^2_{48}}$ and $\mathbf{MCL^2_{26}}$,
- diagonal inhibition textures as $\mathbf{MCL^2_{15}}$ and $\mathbf{MCL^2_{37}}$.

As a next step, the distance of Mean Clique Lengths and Clique Standard Deviations are used to calculate the distance between the textures **T1** and **T2** is, then, given as

$$d(x, y) = \left| \underline{\mathbf{M}}^{n}(T1) - \underline{\mathbf{M}}^{n}(T2) \right| + \left| \underline{\mathbf{C}}^{n}(T1) - \underline{\mathbf{C}}^{n}(T2) \right|$$

The above distance gives us a measure for the similarity of texture **T1** and **T2**. Using this distance, it is possible to classify the textures. Experimental results show that MCL is very successful for identifying visually similar textures. Table 2 shows the most similar five textures according to the Euclidean distance of Mean Clique Lengths. Visual inspection of the textures1-35 and the quantitative analysis of table 2 indicate that the proposed distance is highly consistent with our human visual system in measuring the texture similarity.

6. CONCLUSIONS

In this paper, a set of measures, namely, Mean Clique Length and Clique Standard Deviation, are introduced to measure the similarity of binary textures. Markov Random Fields texture model is used to generate the texture alphabet. This model is capable to generate a wide class of binary textures.

It is intuitively clear that the distribution of different clique types in the image defines texture. Therefore, by using the clique type statistics on a given texture, we can get an idea about the appearance of the texture.

Based on the above argument, we introduce the definitions for base clique, nth order clique, Mean Clique Length (MCL) and Clique Standard Deviation (CSD) measures. MCL and CSD are used to obtain quantitative values about the distribution of the different base cliques. Simulation examples demonstrate that MCL and CSD provide most of the information about the appearance of the texture of an image. Various qualitative texture effects, such as clustering, anisotropic, attraction and repulsion effects are measured by MCL and CSD. The results are very consistent with the human visual system. In conclusion, using the second order statistics of the length of n^{th} order clique chains, visually similar textures can be easily identified.

It is possible to extend the concepts introduced in this paper to a broader class of textures other then MRF. The definitions of MCL and CSD can be extended to gray level and/or color textures. Also, aditional measures, such as, moments can also be used for quantifying the texture similarity.

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Textures 1-35

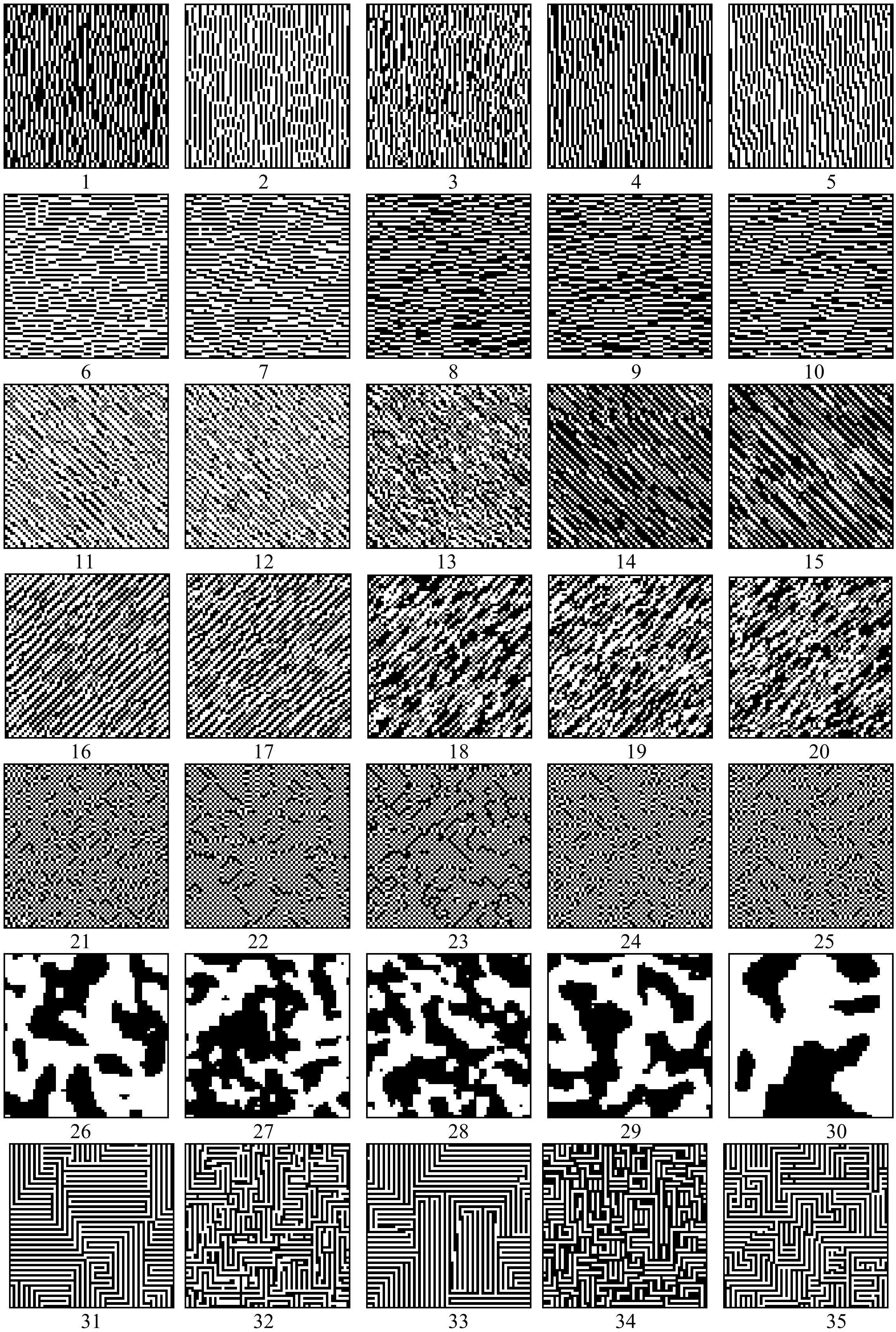

Table 1. The model parameters used in texture generation

Texture No	b0	b1	b2	b3	b4
1	-0,04	3,2	-2	0,1	0,1
2	0,11	4,5	-3,1	-2	-3
3	-0,2	2	-2	0,1	0,1
4	-0,11	8	-4	-3,6	0,2
5	-0,32	1,23	-0,8	-0,78	0,3
6	0,107	-3	4	-2	3
7	0,13	-5	7	-4	0,8
8	-0,06	-2	3	0,1	0,1
9	-0,04	-3	4	0,3	0,1
10	-0,11	-4	8	-3,6	0,2
11	-0,36	-0,6	-0,5	-0,7	1,7
12	-0,6	-1	-1	-1	2,4
13	-0,26	-1,3	-1,3	-0,85	3,5
14	-0,1	-0,3	-0,3	-0,3	1,4
15	-0,13	-0,2	-0,25	-0,28	1.2
16	-0,203	-0,1	-0,5	1,2	-0,4
17	-0,24	-0,5	-0,4	1,7	-0,7
18	-0,126	-0,25	-0,6	1,74	-0,35

Texture No	b0	b1	b2	b3	b4
19	1,68	-1	-1	2	-1
20	-0,17	-0,3	-0,3	1	-0,09
21	5	-2,25	-2,16	0	0
22	3,2	-1,5	-1	0	0
23	1,7	-0,8	-0,4	0	0
24	14,5	-7	-5,5	0	0
25	21	-10	-9	0	0
26	-1,5	0,75	0,75	0	0
27	-3	1,5	1,5	0	0
28	-8	4	4	0	0
29	-2	1	1	0	0
30	-4	2	2	0	0
31	2,19	-0,08	-0,01	-1	-1
32	0,15	2	-2,1	-2	-2,1
33	0,1	3	2,8	-3	-3
34	0,05	7	7	-6	-6
35	1,4	-0,01	-0,01	-0,8	-0,8

Table 2. The most similar five textures.

Texture No	Texture No	Distance	Texture No	Distance	Texture No	Distance	Texture No	Distance	Texture No	Distance
1	3	**0.12**	2	**0.27**	5	**0.33**	4	**0.48**	**34**	**1.37**
2	5	**0.22**	1	**0.27**	3	**0.33**	4	**0.35**	**34**	**1.32**
3	1	**0.12**	2	**0.33**	5	**0.40**	4	**0.56**	**34**	**1.32**
4	5	**0.17**	2	**0.35**	1	**0.48**	3	**0.56**	**34**	**1.64**
5	4	**0.17**	2	**0.22**	1	**0.33**	3	**0.40**	**34**	**1.52**
6	8	**0.28**	9	**0.29**	7	**0.32**	10	**0.39**	**35**	**1.41**
7	10	**0.09**	9	**0.21**	8	**0.27**	6	**0.32**	**35**	**1.69**
8	9	**0.08**	7	**0.27**	6	**0.28**	10	**0.35**	**35**	**1.63**
9	8	**0.08**	7	**0.21**	10	**0.29**	6	**0.29**	**35**	**1.67**
10	7	**0.09**	9	**0.29**	8	**0.35**	6	**0.39**	**35**	**1.74**
11	12	**0.04**	15	**0.13**	14	**0.15**	13	**0.71**	**25**	**1.62**
12	11	**0.04**	14	**0.13**	15	**0.14**	13	**0.68**	**25**	**1.60**
13	14	**0.58**	15	**0.67**	12	**0.68**	11	**0.71**	**25**	**1.09**
14	15	**0.11**	12	**0.13**	11	**0.15**	13	**0.58**	**25**	**1.54**
15	14	**0.11**	11	**0.13**	12	**0.14**	13	**0.67**	**25**	**1.60**
16	17	**0.15**	19	**0.96**	20	**1.16**	18	**1.22**	**21**	**2.02**
17	16	**0.15**	19	**0.83**	20	**1.03**	18	**1.09**	**21**	**1.93**
18	20	**0.17**	19	**0.27**	17	**1.09**	16	**1.22**	**23**	**1.41**
19	20	**0.21**	18	**0.27**	17	**0.83**	16	**0.96**	**21**	**1.44**
20	18	**0.17**	19	**0.21**	17	**1.03**	16	**1.16**	**21**	**1.39**

Texture No	Texture No	Distance	Texture No	Distance	Texture No	Distance	Texture No	Distance	Texture No	Distance
21	24	**0.24**	22	**0.26**	23	**0.35**	25	**0.48**	**20**	**1.39**
22	24	**0.24**	21	**0.26**	23	**0.31**	25	**0.48**	**13**	**1.50**
23	22	**0.31**	21	**0.35**	24	**0.38**	25	**0.61**	**18**	**1.41**
24	22	**0.24**	21	**0.24**	23	**0.38**	25	**0.45**	**13**	**1.51**
25	24	**0.45**	21	**0.48**	22	**0.48**	23	**0.61**	**13**	**1.09**
26	30	**0.47**	28	**0.50**	27	**0.50**	29	**0.58**	**34**	**1.63**
27	30	**0.34**	26	**0.50**	29	**0.58**	28	**0.82**	**34**	**1.46**
28	26	**0.50**	29	**0.71**	27	**0.82**	30	**0.90**	**34**	**1.97**
29	26	**0.58**	27	**0.58**	30	**0.59**	28	**0.71**	**34**	**1.38**
30	27	**0.34**	26	**0.47**	29	**0.59**	28	**0.90**	**34**	**1.27**
31	35	**0.72**	33	**0.72**	32	**0.73**	34	**1.10**	**30**	**1.74**
32	34	**0.44**	33	**0.51**	31	**0.73**	35	**0.74**	**30**	**1.37**
33	32	**0.51**	31	**0.72**	34	**0.83**	35	**0.84**	**30**	**1.64**
34	32	**0.44**	33	**0.83**	35	**0.98**	31	**1.10**	**30**	**1.27**
35	31	**0.72**	32	**0.74**	33	**0.84**	34	**0.98**	**6**	**1.41**