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Classification of Textures by Avoiding Complex Patterns

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Abstract: The present research advocates a new method for texture classification based on primitive patterns. For this, an optimal set of eight simple patterns are selected based on their discrimination. The percentage of frequency of occurrences is computed for these patterns on entire texture image. Textures can be classified by using frequency of occurrences, for complex patterns also. The present research proposes a scheme to completely avoid the computation of, frequency of occurrence for complex patterns. Further, an innovative scheme for determining the percentage of occurrences of upper and lower limits of complex patterns is focused in the present study. The experimental results proved the avoidance of computation of complex patterns. Finally, the experimental results on Brodatz textures indicate the clear classification of textures into classes by selecting simple patterns, but the classes are overlapped when complex patterns are applied.

Key words: Classification, discrimination, classes, simple-patterns, complex-patterns, upper limit, lower limit

INTRODUCTION

Texture discrimination or classification is the basis for many applications in computer vision. Texture classification is an image processing technique by which different regions of an image are identified based on texture properties. This process plays an important role in many industrial, biomedical and remote sensing applications. Under its simpler form, the problem is, to design a method to decide whether two or more given image samples are similar or significantly different from each other. If two or more image samples are similar then they can be classified into same class, or if they are dissimilar then they can be classified into different classes. This classification finally leads into discrimination. Texture is characterized not only by the gray value at a given pixel, but also by the gray value pattern in a neighborhood surrounding the pixel. The ability to efficiently analyze and describe textured pattern is thus of vital importance. A simple or complex pattern of a neighborhood can be considered as one of the textures primitive feature. Textural features can often be used to recognize familiar objects in an image or retrieve images with similar texture from databases. The present paper uses these primitive features of textures to classify the textures. Earlier researchers utilized statistical and structural methods for texture feature extraction[1-4]. Recently[5] proposed pattern based classification methods and also proposed a measure of pattern trends[6] on various types of preprocessed textures. Gaussian Markov random field (GMRF) and Gibbs distribution texture models were developed and used for texture recognition[7,8]. Power spectral methods[1] using the Fourier spectrum have also been used. DCT, Walsh-Hadamard, and DHT have been used for recognition of two-dimensional binary patterns[9]. One of the major developments in texture segmentation is the use of multi-resolution and multi channel descriptions[10] of the texture images. This description provides information about the image contained in every smaller regions of the frequency domain, and thus provides a powerful tool for the discrimination of similar textures. The use of scale-space-filtering is equivalent to a decomposition of the image in terms of wavelets. Several wavelets transform algorithms such as the pyramidal and tree structured wavelet transforms[11-14], Gabor filters[15], and the Haar[16] basis functions are used for multiresolution and multi channel texture classification/ segmentation. Laws[17] proposed a simple scheme which can be used to local linear transformations and energy computation to extract texture features. This simple scheme often

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gives good results but not consistent in performance. The present paper chose classification and discrimination of textures into groups by a simple or primitive patterns of a 3×3 neighborhood. Depending on the context the word pattern has many different interpretations. The biology community seems to use the word pattern without defining it. The implicit meaning generally brings to mind some kind of repeated arrangement (regular or not) and the term is often defined by examples. The word texture certainly has many interpretations in the graphics community. We will use the word texture in the sense of a pattern applied to the surface of an object. Intuitively, we can think of texture as visual information which gives us clues about the nature of the object, usually expressed at the objects surface. The difference between a pattern and a texture is that, a texture involves the attachment of the pattern to the surface of an object.

Using a 3×3 grid, one can generate 512 patterns. However, if we specify the center point of a 3×3 grid should be a grain component, then the number of spatial patterns will be reduced to 256. The present study uses this concept. It is possible to enumerate all the 256 patterns using a 3×3 grid, but such an exhaustive enumeration is removed in the present paper by considering only 8 simple patterns to classify the textures.

MATERIALS AND METHODS

The present study defines the eight simple patterns called Top Horizontal Line (THL), Middle Horizontal Line (MHL), Bottom Horizontal Line (BHL), Left Vertical Line (TVL), Middle Vertical Line (MVL), Right Vertical Line (RVL), Left Diagonal Line (LDL) and Right Diagonal Line (RDL) on a 3×3 neighborhood. The present research identifies a pattern if and only if the central pixel is a grain component. The following Fig. 1 specifies the particular kind of arrangement of the above simple patterns. In the following Fig. 1 the ⊗ specifies a grain or 1 and the symbol d specifies dont care symbol that is either zero or one.

Method of computation of complex patterns from the derived eight simple patterns: In a 3×3 grid a rectangle is formed by the union of any two adjacent vertical or horizontal lines. There are other interesting patterns or shapes like A, B, D, E, F, H, I, L and T which are composed of one or more horizontal and/or vertical lines. Since the present investigation has computed all the horizontal and vertical lines, again

⊗	⊗	⊗
d	⊗	d
d	d	d

(a)

d	d	d
⊗	⊗	⊗
d	d	d

(b)

d	d	d
d	⊗	d
⊗	⊗	⊗

(c)

⊗	d	d
⊗	⊗	d
⊗	d	d

(d)

d	⊗	d
d	⊗	d
d	⊗	d

(e)

d	d	⊗
d	⊗	⊗
d	d	⊗

(f)

⊗	d	d
d	⊗	d
d	d	⊗

(g)

d	d	⊗
d	⊗	d
⊗	d	d

(h)

Fig. 1: Representation of primitive patterns (a): Top horizontal line patterns (b): Middle horizontal line patterns (c): Bottom horizontal line patterns (d): Left vertical line patterns (e): Middle vertical line patterns (f): Right vertical line patterns (g): Left diagonal line patterns (h): Right diagonal line patterns

study of above said patterns forms no meaning. Many types of right angle triangle patterns can be formed on a 3×3 grid. They are mainly composed of horizontal lines, vertical lines and diagonal lines as shown in the Fig. 2.

Based on this simple pattern evaluation the present research evaluates a novel concept that gives the upper limit of percentage of occurrences of some of the complex patterns. The equations can be further extended for other type of complex patterns. For example a square pattern on a 3×3 grid is considered as a group of four simple patterns that are THL, BHL, LVL and RVL. i.e., A square pattern can be formed on a 3×3 grid if all the above four patterns exist in the grid. If one or group of pixel(s) of any one of the above four patterns are not grain, then this results into a non formation of square pattern. Therefore the maximum percentage of frequency occurrence of the square patterns in an image will be less than or equal to minimum of (MPO (THL, BHL, LVL, RVL)).

⊗	⊗	⊗
⊗	⊗	d
⊗	d	d

(a)

d	d	⊗
d	⊗	⊗
⊗	⊗	⊗

(b)

⊗	⊗	⊗
d	⊗	⊗
d	d	⊗

(c)

⊗	d	d
⊗	⊗	d
⊗	⊗	⊗

(d)

Fig. 2: Representation of right angle triangle patterns

The following equations give the upper limit of some of the complex patterns:

$$\mathrm{MPO(Square)} \le \mathrm{Min(MPO(THL, BHL, LVL, RVL))} --- \quad 2$$
$$\mathrm{MPO(Rectangle)} \le \mathrm{Min(MPO(THL, MHL))} ------- \quad 3$$
$$\mathrm{MPO(Rectangle)} \le \mathrm{Min(MPO(MHL, BHL))} ------- \quad 3'$$
$$\mathrm{MPO('A')} \le \mathrm{Min(MPO(THL, MHL, LVL, RVL)} ------ \quad 4$$
$$\mathrm{MPO('B')} \le \mathrm{Min(MPO(THL, MHL, BHL, LVL, MVL))} -- \quad 5$$
$$\mathrm{MPO('C')} \le \mathrm{Min(MPO(THL, BHL, LVL))} --------- \quad 6$$
$$\mathrm{MPO('D')} \le \mathrm{Min(MPO(THL, MHL, BHL, LVL, RVL))} -- \quad 7$$
$$\mathrm{MPO('E')} \le \mathrm{Min(MPO(THL, MHL, BHL, LVL))} ------8$$
$$\mathrm{MPO('F')} \le \mathrm{Min(MPO(THL, MHL, LVL))} --------- 9$$
$$\mathrm{MPO('I')} \le \mathrm{MPO(LVL \,||\, MVL \,||\, RVL))} -----------10$$
$$\mathrm{MPO('L')} \le \mathrm{Min(MPO(BHL, LVL))} ------------ \quad 11$$
$$\mathrm{MPO('U')} \le \mathrm{Min(MPO(BHL, LVL, RVL))} ---------12$$
$$\mathrm{MPO('N')} \le \mathrm{Min(MPO(LVL, RVL, RDL))} ---------13$$
$$\mathrm{MPO('X')} \le \mathrm{Min(MPO(LDL, RDL))} ------------ \quad 14$$
$$\mathrm{MPO('T')} \le \mathrm{Min(MPO(THL, MVL))} ------------15$$

Where MPO denotes the maximum percentage of occurrences. For example Eq. (2) denotes0≤ MPO (Square Patterns)≤min (MPO(THL, BHL, LVL, RVL).

RESULTS AND DISCUSSION

Evaluation: Figure 3 specifies the entire process of classification of textures based on simple patterns. This entire process is repeated for the eight simple patterns and some of the complex patterns on thirteen Brodatz textures as listed in the Table 1. Now onwards the textures will be represented by their number instead of name for convenience sake.

The Table 2 and Table 3 represent the percentage of occurrence of simple patterns and complex patterns respectively for all the 13 textures.

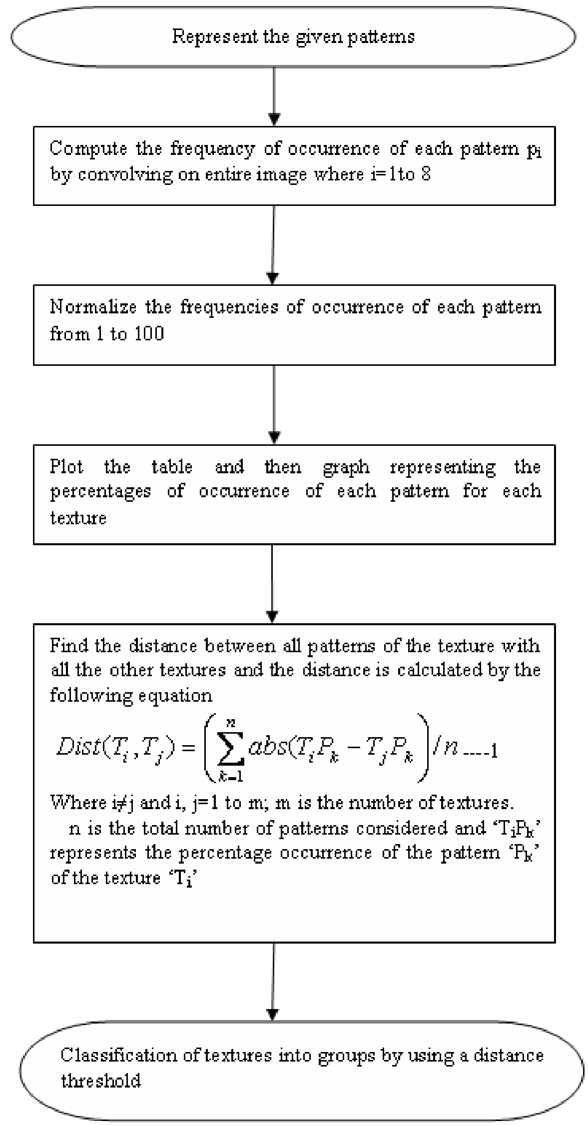

Fig. 3: Block diagram of entire process of classification based on primitive patterns

Table 1: Brodatz Texture.

Texture	Brodatz Texture name
T_1	Bark(D12)
T_2	Beach sand(D29)
T_3	Brick wall(D94)
T_4	Grass(D9)
T5	Herringbone weave(D15)
T_6	Pigskin(D92)
T_7	Plastic bubbles(D112)
T_8	Pressed calf leather(D24)
T_9	Raffia(D84)
T_{10}	Straw(D15)
T_{11}	Water(D38)
T_{12}	Wood grain(D68)
T_{13}	Woolen cloth(D19)

Table 2: Percentage occurrence of simple patterns for all thirteen textures.

	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
T1	33.59	37.15	33.38	36.06	42.23	35.81	33.22	34.87
T2	23.00	30.05	22.81	22.56	29.19	22.60	22.78	26.90
T3	36.43	39.18	36.13	39.71	46.94	40.33	37.37	37.46
T4	19.60	24.93	19.42	20.57	27.97	20.62	21.18	23.31
T5	11.27	18.30	9.73	10.16	19.51	10.99	18.93	19.03
T6	36.75	43.43	37.33	36.85	43.06	37.02	39.58	37.25
T7	27.39	32.08	27.19	27.11	31.62	27.22	26.84	28.83
T8	12.91	15.95	12.30	18.16	28.86	17.70	16.55	15.20
T9	18.31	26.85	18.53	16.00	21.91	16.41	13.72	17.88
T10	22.98	28.18	22.92	23.05	28.52	23.27	20.59	33.35
T11	19.14	21.56	19.23	25.48	38.25	24.69	22.13	20.46
T12	26.06	27.39	25.85	37.73	53.05	37.43	26.76	27.60
T13	26.15	30.28	25.74	26.86	32.29	26.82	26.63	25.96

Table 3: Percentage occurrence of Complex Patterns for all thirteen textures.

	L	X	SQUARE	LORTR	RORTR	T	H	A
T1	26.66	24.95	23.23	26.66	27.17	29.34	23.14	22.37
T2	12.67	11.64	9.21	12.67	14.39	16.18	9.21	8.24
T3	31.49	31.87	29.96	31.49	32.17	33.87	29.70	28.87
T4	11.72	10.77	8.35	11.72	12.46	14.69	8.62	7.61
T5	4.66	3.52	1.86	4.66	4.08	6.24	1.61	1.28
T6	28.13	24.57	21.54	28.13	26.96	29.30	21.58	20.22
T7	20.08	18.15	16.85	20.08	21.00	22.30	16.74	16.20
T8	7.77	6.31	4.54	7.77	6.84	10.39	4.91	4.15
T9	7.89	6.63	5.75	7.89	10.04	10.76	4.98	4.51
T10	12.69	13.92	10.95	12.69	17.45	17.10	11.00	10.26
T11	16.07	14.16	11.70	16.07	14.74	16.74	13.56	12.35
T12	23.00	21.96	20.21	23.00	23.16	24.75	21.43	20.51
T13	18.97	17.12	15.12	18.97	18.65	21.27	15.25	14.36

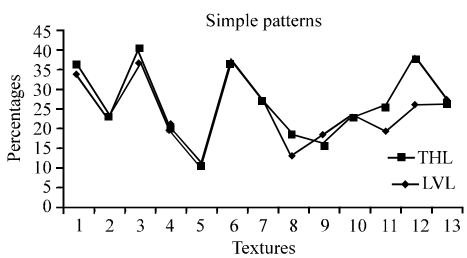

Fig. 4: Classification of textures by individual patterns THL and TVL

The dark (diamond) and light (square) lines of the graph of the Fig. 4 indicates the maximum percentage of occurrence of THL and TVL respectively. The textures T2 and T12 falls into same group by considering THL where as they fall into different groups by considering TVL.

Thats why instead of classifying textures by individual patterns as shown in the Fig. 4, it is appropriate to find the distance function which represents all patterns. By using distance function, overlapping of textures in different groups can be reduced.

From Table 2 and 3 a distance function is computed that computes the distance between all similar patterns of one texture with all other textures and is listed in Table IV and Table V for both simple and complex patterns respectively.

Analysis: The Tables 4 and 5 indicate the distance measure between all thirteen textures with all simple and complex patterns. The diagonal elements of distance Tables 4 and 5 prove the fact that the distance between same textures is zero i.e. DIST $(T_i,T_i) = 0$.

The textures that differ with a distance threshold factor of d can be considered as one class. That is two or more textures can be placed into one class C if each texture differs with all other textures in the group by a distance of less than or equal to d, as specified below.

C = $\{T_i, T_{i+1}, T_{i+2},..., T_n\}$, this is true if and only if for all textures, D $(T_{i,}, T_j) <= d$, where i, j are 1 to n and i $\neq$j.

The distance Table 4 reveals the following texture classification for a unique distance threshold value 6.

C1 = $\{T_1, T3, T6\} <= d_i$
C2 = $\{T_5, T_8\} <= d_i$
C3 = $\{T_2, T_4, T_7, T_{10}, T_{11}, T_{13}\} <= d_i$
C4 = $\{T_{12}\}$

where $d_i <= 6$.

Table 4: Distance function for Simple Patterns.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13
T1	0	11	3	14	21	3	7	19	17	10	12	7	8
T2	11	0	14	3	10	14	4	8	6	2	5	8	3
T3	3	14	0	17	24	2	11	22	20	14	15	8	12
T4	14	3	17	0	7	17	6	5	4	3	3	11	5
T5	21	10	24	7	0	24	14	5	6	11	9	18	13
T6	3	14	2	17	24	0	10	22	20	14	15	9	11
T7	7	4	11	6	14	10	0	11	10	4	6	6	1
T8	19	8	22	5	5	22	11	0	5	8	7	16	10
T9	17	6	20	4	6	20	10	5	0	7	6	14	9
T10	10	2	14	3	11	14	4	8	7	0	5	9	4
T11	12	5	15	3	9	15	6	7	6	5	0	9	5
T12	7	8	8	11	18	9	6	16	14	9	9	0	6
T13	8	3	12	5	13	11	1	10	9	4	5	6	0

Table 5: Distance function for Complex Patterns.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13
T1	0	14	6	15	22	1	7	19	18	12	11	3	8
T2	14	0	19	1	8	13	7	5	4	1	3	10	6
T3	6	19	0	20	28	6	12	25	24	18	17	9	14
T4	15	1	20	0	7	14	8	4	3	3	4	12	7
T5	22	8	28	7	0	22	15	3	4	10	11	19	14
T6	1	13	6	14	22	0	6	18	18	12	11	3	8
T7	7	7	12	8	15	6	0	12	12	6	5	3	1
T8	19	5	25	4	3	18	12	0	1	7	8	16	11
T9	18	4	24	3	4	18	12	1	0	6	7	15	10
T10	12	1	18	3	10	12	6	7	6	0	2	9	4
T11	11	3	17	4	11	11	5	8	7	2	0	8	3
T12	3	10	9	12	19	3	3	16	15	9	8	0	5
T13	8	6	14	7	14	8	1	11	10	4	3	5	0

The study of distance function of complex pattern of Table 5 depicts the following texture classes for a unique distance threshold value 6.

$C1 = \{T_1, T_3, T_6\} <= d_i$
$C2 = \{T_2, T_4, T_8, T_9\} <= d_i$
$C3 = \{T_5, T_8, T_9\} <= d_i$
$C4 = \{T_6, T_7, T_{12}\} <= d_i$
$C5 = \{T_2, T_4, T_9, T_{10}, T_{11}\} <= d_i$
$C6 = \{T_2, T_{10}, T_{11}, T_{13}\} <= d_i$

Here texture T_{12} is not placed in C1 because T_{12} differs with T_1 and T_6 with a distance threshold value <=6. However T_{12} and T_3 differ with a distance threshold of > 6.

CONCLUSION

The results of classification indicate a clear classification of four classes of textures using simple patterns. However the same resulted in six classes of classification using complex patterns. And however this classification is not clear because some of the texture fall into two or more classes and these results into an overlapping among classes of textures. For example T_2 falls into class2, class55 and class6 (C2, C5 and C6). T_8 falls into C2 and C3.T_9 falls into C2, C3 and C5.T_{10} and T_{11} falls into C5 and C6. To cover all textures, six classes are required using complex patterns. Finally the present study concludes that it is always better to classify textures based on above simple patterns, to overcome the overlapping of textures into different classes.

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