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An Innovative Technique of Texture Classification and Comparison Based on Long Linear Patterns

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Abstract: The present paper proposes a method of texture classification based on long linear patterns. Linear patterns of long size are bright features defined by morphological properties: linearity, connectivity, width and by a specific Gaussian-like profile whose curvature varies smoothly along the crest line. The most significant information of a texture often appears in the occurrence of grain components. That's why the present paper used sum of occurrence of grain components for feature extraction. The features are constructed from the different combination of long linear patterns with different orientations. These features offer a better discriminating strategy for texture classification. Further, the distance function captured from the sum of occurrence of grain components of textures is expected to enhance the class seperability power. The class seperability power of these features is investigated in the classification experiments with arbitrarily chosen texture images taken from the Brodatz album. The experimental results indicated good analysis, and how the classification of textures will be effected with different long linear patterns.

Keywords: Orientations, Linearity, Connectivity, Features.

INTRODUCTION

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 areas such as industrial automation, biomedical image processing, Content Based Image Retrieval and remote sensing application. In spite of the importance of textures in many areas of image processing, there is no universally accepted definition for the texture. We prefer to adopt the definition suggested in ^[1], because of its generality and it is given as follows: "The notion of texture appears to depend upon three ingredients: (i) some local 'order' is repeated over a region which is large in comparison to the order's size, (ii) the order consists in the nonrandom arrangement of elementary parts, and (iii) the parts are roughly uniform entities having approximately the same dimensions everywhere within the textured region".

This definition explains that the texture is characterized not only by gray value at a given pixel, but also by the gray value pattern in the surrounding pixels. The texture has both local and global meaning, in the sense

that it is characterized by the invariance of certain local attributes that are distributed over a region of an image ^[2]. To design an effective algorithm for texture classification, it is essential to find a set of texture features with good discriminating powers. Most of the textural features are generally obtained from the application of a local operator, statistical analysis, or measurement in a transformed domain. Generally, the features are estimated from co-occurrence matrices. Law's texture energy measures, Fourier transform domain, Markov random field models, local linear transforms etc. A number of texture classification techniques are reported in literature ^[3, 4, 5, 6]. The wavelet methods ^[3, 6, 7] offer computational advantages over other methods for texture classification and segmentation. In ^[8], Haralick features ^[9] are obtained from wavelet decomposed image yielding improved classification rates. In ^[10], texture features are characterized by considering intensity and contextual information obtained from binary images. The conditional co-occurrence histograms are computed

Corresponding Author: Dr. V. Vijaya Kumar, Dean and Professor of CSE & IT, Godavari Institute of Engineering and Technology, N.H.-5, Chaitanya Nagar, Rajamundary, East Godavari (Dist), Andhra Pradesh, India. Pin: 533 294. Tel.:+91-9849452287 from the intensity and binary images. To obtain binary images the fixed thresholds were used. It is evident that the context or the position information of a pixel in an image is very important for the purpose of classification.

In this, paper, we propose a novel scheme of texture classification based on sum of occurrences of grain components in long linear patterns (LLP) with different orientations.

This paper is organized as follows: In section 2, we briefly review theory of linear patterns. The methodology of feature extraction and distance function are evaluated in section 3. The analysis on texture classification based on experimental results is presented in section 4. Concluding remarks are given in section 5.

LONG LINEAR PATTERNS (LLP)

The linear elements considered in the present paper are long one-dimensional line elements or patterns or structuring elements. The one-dimensional LLP play a significant role in many image processing operations, such as segmentation, edge detection, classification etc. Moreover line structuring elements are more suited for many morphological operations. In some image processing applications, the square, hexagon, and octagon patterns are used. However the above patterns can be easily decomposed into two, three and four line segments respectively ^[11, 12]. The advantage of using one dimensional line pattern segments instead of Ndimensional structuring elements is a reduction in the computational complexity.

In the present paper LLP on the texture images are computed basically by using Bresenham's line algorithm ^[13]. Bresenham ^[13] published an algorithm to draw a line segment of any size and of any orientation on a plotter, which could draw horizontal, vertical and diagonal lines. The algorithm combines small portions of these lines to form a line pattern of any orientation. In image processing, Bresenham lines are formed by steps in the eight cardinal directions of the grid. But true line patterns can be formed by using Bresenham's line algorithm, for the lines on X axis, Y axis and X=Y axis, i.e. the lines with 0^0 , 180^0 , 90^0 , 270^0 , 45^0 , 135^0 , 225^0 , 315^0 . For all other orientation, the shape of the LLP appears as steps of a stair case, known as Jaggies.

The LLPs of size 1×11 with 0^0 , 15^0 , 30^0 and 45^0 orientations are shown in the following Fig. 1(a), 1(b), 1(c) and 1(d) respectively. The following figures clearly indicate that the LLP length, defined by an integer number of pixels, depends on the degree of orientation. Each degree of orientation of the LLP will have a



Fig. 1: LLP of Size 1x11 (a) 0^{0} orientation. (b) 15^{0} orientation. (c) 30^{0} orientation. (d) 45^{0} orientation.

different set of lengths. The present paper assumes the orientation of LLP as triangular shape shown in Fig.2, but not as a semi circle. This is one of the reasons why



Fig. 2: The structure of long linear pattern with different orientations.

length of the LLP is reduced for orientations other than X axis and Y axis. For example the LLP 1x11, is having length 11, 11, 9 and 9 for 0^0 , 15^0 , 30^0 and 45^0 orientations respectively. The length is decreased for 30^0 and 45^0 orientation because of the triangular orientation as shown in Fig.2. Where as the exact length of 11 pixels are resulted for the 0^0 and 15^0 orientation, as shown in the Fig.1 (a) and 1(b) respectively. This is because 0^0 orientation falls on X-axis and 15^0 orientation is very closer to X-axis.

METHODOLOGY

The present paper is not concentrated in studying the frequency of occurrence of one dimensional LLP on the texture image because their frequency occurrences will be minimum (most of the times one digit). The classification may become a problem if the frequency count is low. Moreover the most significant information of a texture appears in the occurrence of grain components. That's why the present paper had chosen the sum of occurrence of grain components of LLP as feature extraction. For this one dimensional LLP's of different sizes 1x11, 1x13, 1x15, and 1x17 are chosen. The above LLP's are rotated for every 15^0 from 0^0 to 90° . The change of topology on LLP with respect to summation of number of occurrences, of grain components are counted, as shown in Fig.1. This experiment is carried out on thirteen Brodatz textures and is listed from Table 3 to Table 6. In order to classify the textures a distance function is used in the present paper. The distance function is calculated in the following way.

Table 1: Distance function with orientations.

Name of Texture	GX_1^{o}	GX_2^{o}	 $GX_n^{\ o}$
T_1	A_1	A_2	 A _n
T_2	B_1	B_2	 $\mathbf{B}_{\mathbf{n}}$
Distance between Textures with same orientations.	A ₁ -B ₁	A ₂ -B ₂	 A _n -B _n

$$D(T_1, T_2) = \sum_{i=1}^{n} (ABS(A_i - B_i)^2)$$

where GX_1° represents the total number of occurrences of grain components by X_i° , of texture T_k And D (T_1 , T_2) is the absolute overall difference between the textures T_1 and T_2 . The entire process of enumerating the classification of texture is listed in the Fig. 3.



Fig. 3: Block diagram of entire process.

Ta	ble	2:	Broda	tz 7	fexture.
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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)

RESULTS AND ANALYSIS

RESULTS: The above scheme of classification is applied on randomly chosen 13 Brodatz textures as given in Table 2. Here on wards the texture number is presented instead of texture name. The Tables 3, 4, 5 and 6 gives the sum of grain components of LLP 1x11, 1x13, 1x15 and 1x17 respectively for all 13 textures with orientations ranging from 0^0 to 90^0 for every 15^0 .

ANALYSIS: The Tables 7, 8, 9 and 10 indicate the distance measure between all thirteen textures in all orientations, of LLP of size 1x11, 1x13, 1x15 and 1x17 respectively. The diagonal elements of all distance Tables 7, 8, 9 and 10 prove the following 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, $D(T_{i,}, T_j) \le d$, where i, j are 1 to n and $i \ne j$.

The following analysis on classification of textures for all LLP's has been done with the same distance threshold value 20. Careful analysis of Table 7, of LLP 1x11 reveals the following texture classification for a unique distance threshold value, 20.

 $C_1 = \{T_1, T_2, T_3, T_{10}, T_{12}\} \le d_i$

$$C2 = \{T_{4}, T_{5}, T_{7}, T_{8}, T_{9}, T_{11}, T_{13}\} \le d_{i}$$

 $C3 = \{T_6\}$

Table 3: Sum of occurrence of grain components for LLP of size 11

	T1	T2	Т3	T4	T5	T6	T7	T8	Т9	T10	T11	T12	T13
SE0 ⁰	247,518	240,465	248,436	221,497	226,064	272,382	209,561	216,544	213,224	233,622	216,200	247,917	218,532
SE15 ⁰	245,853	238,906	246,746	220,147	224,614	270,653	208,127	215,157	211,773	232,168	215,127	246,095	216,782
SE30 ⁰	201,351	195,778	202,112	180,453	183,913	222,417	170,377	176,198	173,283	190,236	176,059	201,757	177,752
SE45 ⁰	197,506	191,895	198,670	177,090	180,488	219,626	167,110	172,747	169,967	186,710	172,755	197,405	174,755
SE60 ⁰	199,761	194,006	200,118	179,066	182,296	221,964	168,826	174,429	171,779	188,600	174,417	200,121	176,389
SE75 ⁰	247,007	239,728	246,198	221,634	224,755	275,278	208,660	214,834	211,905	232,854	215,523	248,526	217,687
SE90 ⁰	249,649	242,514	249,630	224,138	227,081	278,198	211,234	216,804	213,663	235,236	217,672	252,207	219,635

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Table 4.	Sum of	occurrence of	t orain	components	tor	TIP	01 \$170	1.5
ruore r.	oum or	occurrence of	i zium	componentos	TOT			1.

	T1	T2	Т3	T4	T5	T6	T7	T8	Т9	T10	T11	T12	T13
SE0 ⁰	289,428	280,932	290,640	258,735	264,411	318,465	245,154	253,159	249,514	273,292	253,023	289,423	255,720
SE15 ⁰	284,727	276,459	286,365	254,793	260,416	314,420	241,222	249,245	245,636	269,306	249,504	284,309	251,744
SE30 ⁰	241,205	234,293	242,780	216,076	220,541	267,203	204,203	211,121	207,890	228,132	211,173	240,929	213,442
SE45 ⁰	197,506	191,895	198,670	177,090	180,488	219,626	167,110	172,747	169,967	186,710	172,755	197,405	174,755
SE60 ⁰	241,747	234,673	242,150	216,787	220,608	269,609	204,258	211,057	207,823	228,320	211,077	241,801	213,699
SE75 ⁰	285,907	277,346	285,364	256,574	260,461	319,893	241,470	249,083	245,390	269,899	249,530	286,260	252,533
SE90 ⁰	292,108	283,557	292,189	262,310	265,582	326,559	247,106	253,545	249,942	275,338	254,597	294,597	257,155

Table 5: Sum of occurrence of grain components for LLP of size15

			0	1									
	T1	T2	Т3	T4	T5	T6	T7	T8	Т9	T10	T11	T12	T13
SE0 ⁰	330,432	320,420	331,762	295,014	301,897	363,458	280,008	288,992	285,123	312,156	289,043	330,030	292,051
SE15 ⁰	325,080	315,351	326,887	290,538	297,355	358,831	275,551	284,551	280,714	307,647	285,064	324,230	287,508
SE30 ⁰	281,978	273,643	283,969	252,328	257,870	312,412	238,839	246,745	243,220	266,822	247,039	281,177	249,728
SE45 ⁰	236,453	229,511	238,362	211,972	216,225	263,889	200,148	206,845	203,723	223,735	207,026	235,495	209,708
SE60 ⁰	279,697	271,440	281,559	250,903	255,388	313,118	236,549	244,450	240,562	264,563	244,538	278,572	247,906
SE75 ⁰	326,587	316,618	326,018	293,079	297,367	366,134	275,777	284,318	280,172	308,408	284,910	326,357	288,662
SE90 ⁰	333,678	323,707	333,845	299,639	303,230	373,769	282,224	289,416	285,383	314,621	290,683	335,922	293,960

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Table 6	Sum of	occurrence	ΩŤ	orain	components	tor	I I P	01 \$170	1/
rable 0.	Duni Or	occurrence	O1	Siam	componentis	101		OI BILC	1/

	T1	T2	Т3	T4	T5	Τ6	T7	T8	Т9	T10	T11	T12	T13
SE0 ⁰	370,435	358,979	371,812	330,319	338,491	407,420	314,023	324,006	319,966	350,200	324,256	369,658	327,545
SE15 ⁰	364,347	353,224	366,320	325,218	333,324	402,222	308,983	318,969	314,969	345,110	319,695	363,082	322,481
SE30 ⁰	318,850	309,044	321,297	285,064	291,717	354,326	270,162	278,937	275,281	301,986	279,641	317,181	282,701
SE45 ⁰	273,760	265,301	276,159	245,202	250,264	306,458	231,788	239,329	235,981	259,263	239,828	271,706	243,119
SE60 ⁰	319,516	309,860	321,677	286,623	291,598	358,391	270,156	279,051	274,700	302,358	279,209	317,608	283,388
SE75 ⁰	366,426	355,050	365,970	328,768	333,554	411,186	309,420	318,745	314,146	346,132	319,472	365,481	323,976
SE90 ⁰	374,388	362,965	374,572	336,117	340,091	419,756	316,605	324,439	320,016	353,071	325,963	376,184	329,954

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Table 7.	Distanc	es betwe	en lexiu	ies using	LLF 01	SIZE II.							
	T ₁	T ₂	T ₃	T ₄	T₅	T ₆	T 7	T ₈	T9	T ₁₀	T ₁₁	T ₁₂	T ₁₃
T ₁	0	6	0	48	38	38	91	65	91	16	58	0	53
T.	6	0	6	22	16	72	53	33	53	4	28	6	25
т Т	0	6	0	10	20	20	01	65	01	16	59	0	52
13 T	10	0	10	40	30	170	51	00	51	10	50	0	33
14	48	22	48	0	2	170	1	3	1	10	2	48	1
T ₅	38	16	38	2	0	150	13	5	13	6	4	38	3
T ₆	38	72	38	170	150	0	245	201	245	100	188	38	179
T ₇	91	53	91	7	13	245	0	4	0	33	5	91	6
T.	65	33	65	3	5	201	4	0	4	19	1	65	2
т.	91	53	91	7	13	245	0	4	0	33	5	91	6
- '9 -	10	4	10	10	0	100	0	10	0	00	10	10	10
1 ₁₀	10	4	10	10	0	100	33	19	33	0	10	16	13
I ₁₁	58	28	58	2	4	188	5	1	5	16	0	58	1
T ₁₂	0	6	0	48	38	38	91	65	91	16	58	0	53
T ₁₃	53	25	53	1	3	179	6	2	6	13	1	53	0
Table 8:	Distanc	es betwe	en textu	res using	LLP of	size 13.							
	T ₁	T ₂	T ₂	T ₄	T ₆	Τ¢	T-	Т。	T۵	T10	T11	T12	T12
т.	0	6	- 3	10	20	65	11/	9/	9/	12	9/	0	70
-	0	0	-	40	30	65	70	04	04	13	04	0	70
12	6	0	1	24	16	107	72	48	48	3	48	6	38
T ₃	1	7	0	55	43	60	123	91	91	16	91	1	77
T ₄	48	24	55	0	2	223	16	6	6	13	6	48	4
T₅	38	16	43	2	0	199	22	10	10	7	10	38	6
T,	65	107	60	223	199	0	349	295	295	132	295	65	267
 т	114	70	100	16	20	240	010	4	1	50	1	114	201
17 T	114	12	123	10	22	349	0	4	4	00	4	114	6
8	84	48	91	6	10	295	4	0	0	33	0	84	2
T9	84	48	91	6	10	295	4	0	0	33	0	84	2
T ₁₀	13	3	16	13	7	132	53	33	33	0	33	13	25
T 11	84	48	91	6	10	295	4	0	0	33	0	84	2
T	0	6	1	48	38	65	114	84	84	13	84	0	70
T	70	20	-	40	6	00	6	0	0	25	0	70	0
13	70	30	11	4	0	207	0	2	2	25	2	70	0
T 1 1 0	D !												
Table 9:	Distanc	es betwe	en textu	res using	LLP of	<u>size 15.</u>						_	
	1	12	3	4	5	6	17	8	9	I 10	I ₁₁	I 12	13
T ₁	0	7	0	77	48	72	148	116	130	25	107	2	91
T ₂	7	0	7	38	19	123	91	67	77	6	60	9	48
T ₃	0	7	0	77	48	72	148	116	130	25	107	2	91
T,	77	38	77	0	5	295	13	5	7	16	4	77	2
т.	10	10	10	5	0	226	20	16		5	12	50	- 7
15 T	40	100	40	005	0000	230	20	000	22	170	15	30	/
6	72	123	72	295	236	0	424	368	392	179	353	72	323
T 7	148	91	148	13	28	424	0	4	2	53	5	150	7
T ₈	116	67	116	5	16	368	4	0	2	35	1	116	3
Тя	130	77	130	7	22	392	2	2	0	43	3	130	5
T ₁₀	25	6	25	16	5	179	53	35	43	0	30	27	22
T	107	60	107	1	12	353	5	1	2	30	۰ ۵	100	2
•11 •	0	00	0	+ 77	10 E0	70	150	110	100	07	100	03	<u>~</u>
I 12	2	9	2	11	50	12	150	116	130	27	109	U	93
T ₁₃	91	48	91	2	7	323	7	3	5	22	2	93	0
TT 1 1 10	D' 4	1 /			TTD	c · 17							
Table IC	<u>): Distar</u>	ices betw	een text	ures usin	Ig LLP O	$\frac{1}{2}$						_	
	T ₁	T ₂	T ₃	T4	T ₅	T ₆	T ₇	T ₈	Tg	T ₁₀	T ₁₁	T ₁₂	T ₁₃
T ₁	0	6	2	72	65	114	188	132	161	22	123	1	114
T ₂	6	0	10	38	33	168	130	84	107	6	77	9	70
T.	2	10	0	84	77	100	208	148	179	28	139	3	130
т	- 70	20	g <i>1</i>	0		360	200	10	10	16		70	6
14 T	12	00	77	4	і С	0.47	20	10	10	10	10	70	7
15	65	33	11	1	0	347	33	13	22	13	10	12	/
T ₆	114	168	100	362	347	0	590	488	541	232	469	105	452
T ₇	188	130	208	28	33	590	0	6	3	84	7	199	10
T ₈	132	84	148	10	13	488	6	0	3	48	1	143	2
~	-	107	179	19	22	541	3	3	0	67	4	172	5
T	161				10	000	9/	19	67	0	10	27	20
T9 T	161	6	20	10	1.7		- /1		n /			~ /	
T9 T10	161 22	6	28	16	13	232	-	40	07	40	40	27	30
Τ ₉ Τ ₁₀ Τ ₁₁	161 22 123	6 77	28 139	16 7	13 10	232 469	7	1	4	43	43 0	132	1
T9 T10 T11 T12	161 22 123 1	6 77 9	28 139 3	16 7 79	13 10 72	232 469 105	7 199	1 143	4 172	43 27	0 132	132 0	1 123
T9 T10 T11 T12 T13	161 22 123 1 114	6 77 9 70	28 139 3 130	16 7 79 6	13 10 72 7	232 469 105 452	7 199 10	48 1 143 2	4 172 5	43 27 38	0 132 1	132 0 1 <u>23</u>	1 123 0
T_9 T_{10} T_{11} T_{12} T_{13}	161 22 123 1 114	6 77 9 70	28 139 3 130	16 7 79 6	13 10 72 7	232 469 105 452	7 199 10 637	1 143 2	4 172 5	43 27 38	43 0 132 1	132 0 123	1 123 0

Table 7. Distances between textures using LLP of size 11

where $d_i = 20$

The study of distance function Table 8 of LLP 1x13 depicts the following texture classes for a distance threshold value of 20.

 $C1 = \{T_1, T_2, T_3, T_{10}, T_{12}\}$ $C2 = \{T_4, T_7, T_8, T_9, T_{11}, T_{13}\}$

 $C3 = \{T_5\}$

 $C4 = \{T_6\}.$

Here texture T_5 is not placed in class C2 because T_5 differs with T_7 , a distance threshold value greater than 20. However T_5 differs with all other textures of C2 by a distance factor less than 20.Therefore the other way of writing class C3 is

 $C3 = \{T_1, T5, T8, T9, T11, T13\}.$

The clear observation of distance function in Table 9 of LLP 1x15 depicts the following texture classes for a distance threshold value of 20.

 $\begin{array}{l} C1 = \{T_1, T_2, T3, T_{12}\}\\ C2 = \{T_4, T_7, T_8, T_9, T_{11}, T_{13}\}\\ C3 = \{T_5\} \text{ or } \{T_4, T_5, T_8, T_9, T_{11}, T_{13}\}\\ C4 = \{T_6\}\\ C5 = \{T_{10}\}. \end{array}$

The examination of distance function Table 10 of LLP 1x17 depicts the following texture classes for a distance threshold value of 20

 $\begin{array}{l} C1 = \{T_1, T_2, T_3, T_{12}\}\\ C2 = \{T_4, T_8, T_9, T_{11}, T_{13}\}\\ C3 = \{T_5\} \text{ or } \{T_4, T_5, T_8, T_{11}, T_{13}\}\\ C4 = \{T_7\} \text{ or } \{T_7, T_8, T_9, T_{11}, T_{13}\}\\ C5 = \{T_{10}\}\\ C6 = \{T_6\}. \end{array}$

CONCLUSIONS

The analysis about distance functions of LLP concludes that the number of overlapping texture classes will be more by increasing the linear element size. The texture groups or classes are very concise by LLP of size 1x11. The sum of the grain components of large linear patterns 1x11, 1x13, 1x15 and 1x17 as listed in the Tables 3,4,5 and 6 respectively indicates a decreasing trend from 0^0 to 45^0 and an increased trend from 45^0 to 90^0 of grain components. This clearly reflects the geometrical property on linearity that is reflection about the line X = Y. From this the present paper concludes that, it is not necessary to compute the orientations of linear patterns from 90^0 to 360^0 , as they can be counted merely by reflection of X axis and Y axis.

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