A Measure of Pattern Trends on Various Types of Preprocessed Textures

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Summary:
Study of different patterns on a local neighborhood of a texture plays an important role in characterization, and classification of the textures. Many preprocessing steps are used in the generation of textures for a better quality. The present paper studies how the percentage of occurrence factor of a typical pattern varies after applying various local preprocessing steps. For this eight simple patterns are chosen on a 3x3 neighborhood. The simple patterns are chosen in such a way that any complex pattern can be formed by grouping one or more of these simple patterns. The pattern occurrence factor of preprocessed images are also compared with the actual texture images, where no preprocessing is applied. The experimental results on thirty brodatz textures indicate good comparison of variation of occurrence in these patterns on different methods of preprocessed steps of the texture.

Key Words:
Simple-Patterns, Local pre-processing Classification, Frequency of occurrence, Complex-Patterns, Characterization

1. Introduction

Study of patterns on textures is recognized as an important step in characterization and classification of texture. Various approaches are existing to investigate the textural and spatial structural characteristics of image data, including measures of texture [2], Fourier analysis [3], [4], fractal dimension [5], variograms [6]–[10], and local variance measures [1]. Fourier analysis is found as the most useful when dealing with regular patterns within image data. It has been used to filter out speckle in radar data [11] and to remove the effects of regular agricultural patterns in image data [11]. Study of regular patterns based on fundamentals of local variance was carried out recently [12].

Hence, the study of patterns still plays a significant area of research in classification and characterization of textures. That's why the present paper investigates how the frequency of occurrences of patterns varies after applying the reprocessing steps on the original textured image.

The present paper assumes 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 patterns is thus of fundamental importance. A simple or complex pattern of a neighborhood can be considered as one of the texture primitive feature. Textural patterns can often be used to recognize familiar objects in an image or retrieve images with similar texture from a database. However sometimes the textured image obtained may not be of good quality. To enhance the quality or better illumination or contrast or sharpening, some preprocessing steps will be performed on textured data. By these local preprocessing steps there are chances of variation of occurrences of patterns, which may lead to different types of classification of textures based on the preprocessing method adopted. The present paper based on this assumption investigated how the frequency of occurrence of simple patterns varies from one pre-processed image to other.

2. Methodology

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. 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.

The present paper considers a pattern when the central pixel is necessarily a grain component. On these binary images the occurrence of simple patterns like Top Horizontal Line (THL), Middle Horizontal Line (MHL), Bottom Horizontal Line (BHL), Left Vertical Line (LVL), Middle Vertical Line (MVL), Right Vertical Line (RVL), Left Diagonal (LD), and Right Diagonal (RD) are studied. The Fig.1 specifies the particular kind of arrangement of the above simple patterns. In the Fig.1

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the '⊗' specifies a grain or 1 and the symbol d specifies don't care symbol that is either zero or 1.

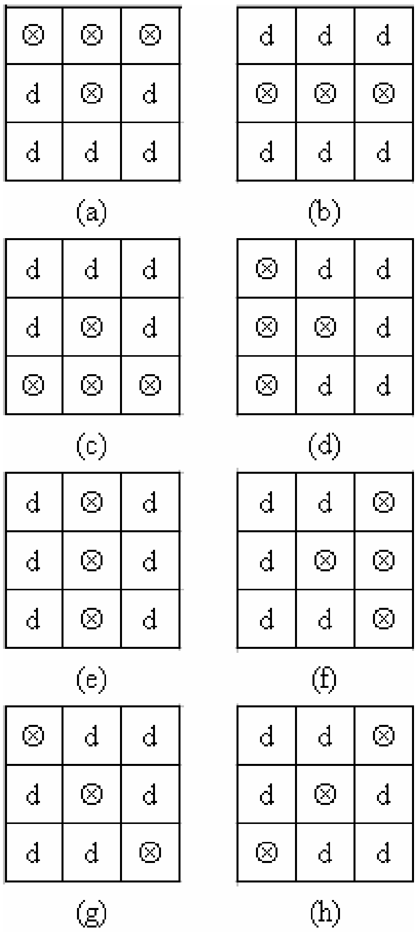

Fig. 1. Representation of Primitive Patterns (a) Top Horizontal Line Patterns (b) Middle Horizontal Line Patterns (c) Bottom Horizontal Line Patterns (d) Left vertical Line Patterns (e) Middle Vertical Line Patterns (f) Right Vertical Line Patterns (g) Left Diagonal Line Patterns (h) Right Diagonal Line Patterns.

2.1 Method of computation of complex patterns from the derived eight simple patterns: In a 3 x 3 grid a rectangle is formed by the union of any two adjacent vertical or horizontal lines. In the same way a square pattern is composed of top and bottom horizontal lines and left and right vertical 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 study of above said patterns forms no meaning. Many types of right angle triangle patterns can be formed on a 3x3 grid. They are mainly composed of horizontal lines, vertical lines and diagonal lines.

The algorithms, shown in Fig. 2 and Fig. 3 give the basic steps that are required to transforming a gray level image into a binary image by using global average, and algorithm that specifies how to apply various preprocessing steps in the given gray level image, respectively.

```
input:  gray level image
output: binary image

begin
        sum=0; globavg =0;

        for i = 1 to n
          for j = 1 to m
              begin
                 sum = sum + grayimage[i,j];
              end

        globavg = (int) (sum/(n*m));

        for i = 1 to n
          for j = 1 to n
            begin
                if ( grayimage[i,j]  ≥ globavg )
                    binimage[i,j] = 1;
                else
                     binimage[i,j] = 0;
            end
end
```

Fig. 2. Algorithm for transforming grey level image to binary by using global average.

```
input: given gray level image
output: preprocessed gray level image

begin
  s = 0; a = 0;
   for i = 2 to n-1
    for j = 2 to m-1
     begin
      for k = i-1 to i+1
        for l = j-1 to j+1
        begin
        localmax[i-1,j-1] = max[grayimage[k,l]];
        localmin[i-1,j-1] = min[grayimage[k,l]];
        localmean[i-1,j-1] = mean[grayimage[k,l]];
        localmedian[i-1,j-1] = median[grayimage[k,l]];
        localmode[i-1,j-1] = mode[grayimage[k,l]];
        localstd[i-1,j-1] = std[grayimage[k,l]];
        localvariance[i-1,j-1] = variance[grayimage[k,l]];
        end
     end
end
```

Fig. 3. Algorithm for applying seven preprocessing steps on gray level image.

where grayimage[n, m] is the two dimensional array consists of the original gray image, localmax [n-1,m-1]……localvariance[n-1,m-1] are 2-D arrays containing preprocessed gray level images.

The present paper investigated the variation of above simple patterns on seven local preprocessed images namely Local Max, Local Minimum, Local Mean, Local Median, Local Mode, Local standard deviation and Local Variance. The entire scheme is explained in the Fig.4. The algorithm in Fig.3 is applied on gray level Brodatz textured image, from which seven preprocessed textured images as mentioned above are obtained. The preprocessed gray levels are converted into binary images. On these binary images percentage of frequency of occurrences of simple patterns are evaluated for 30 textures. However for experimental sake we are listing for four textures as shown in Table 1, 2, 3 and 4. The Percentage of occurrences of patterns are calculated individually. For example the percentage of occurrence of Top Horizontal Lines(THL) are obtained by calculating total number of THL that can be formed on a 3x3 grid on the entire texture image versus the actual number of THL presented in the given texture image.

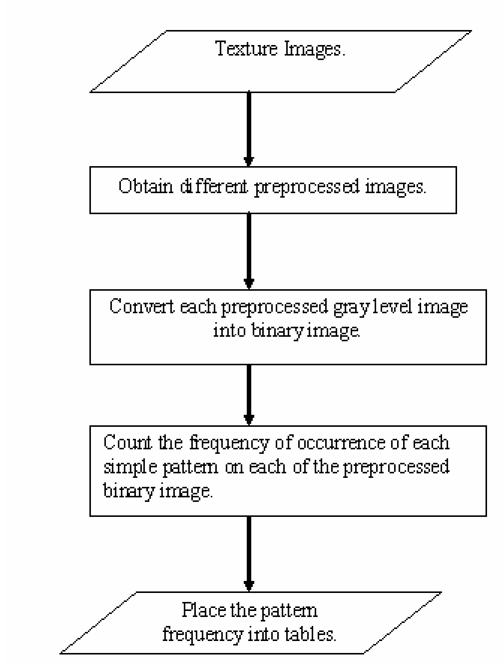

Fig.4. Block diagram of entire process of study of patterns.

Table 1: Frequency of Patterns for Bark Texture.

	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
Original	33.59	37.15	33.38	36.06	42.23	35.81	33.22	34.87
LocalMax	47.49	50.47	47.34	49.50	54.61	49.43	45.41	46.95
LocalMin	37.84	40.93	37.83	39.51	44.47	39.56	36.07	36.46
LocalMean	42.60	44.70	42.57	44.84	49.24	44.76	40.89	42.00
LocalMedian	43.25	45.31	43.12	45.42	49.79	45.34	41.43	42.66
LocalMode	34.29	37.80	34.36	35.77	40.88	35.79	33.10	33.85
LocalSTD	28.68	34.29	28.71	30.93	39.31	31.06	30.55	31.11
LocalVariance	24.44	29.91	24.56	26.81	35.11	26.93	26.23	26.88

Table 2: Frequency of Patterns for Beach Sand Texture.

	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
Original	23.00	30.05	22.81	22.56	29.19	22.60	22.78	26.90
LocalMax	43.42	48.71	43.42	43.41	48.74	43.41	41.03	42.59
LocalMin	37.87	44.14	37.81	37.56	43.53	37.54	34.67	36.31
LocalMean	43.01	47.59	43.00	42.98	47.52	43.05	40.10	43.47
LocalMedian	43.07	47.52	42.98	42.79	47.26	42.99	39.94	43.47
LocalMode	28.54	34.83	28.51	28.38	34.60	28.43	27.66	28.97
LocalSTD	23.65	30.60	23.86	23.39	29.78	23.46	23.79	24.87
LocalVariance	18.03	24.38	18.18	17.84	23.67	17.75	17.96	19.04

Table 3: Frequency of Patterns for Brick Wall Texture.

	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
Original	36.43	39.18	36.13	39.71	46.94	40.33	37.37	37.46
LocalMax	43.84	45.30	43.71	47.12	52.54	47.52	43.20	43.11
LocalMin	49.91	51.64	49.84	53.37	59.36	53.57	49.03	49.04
LocalMean	47.94	49.08	47.83	51.58	57.09	51.74	47.31	47.35
LocalMedian	49.75	50.98	49.60	53.07	58.44	53.42	49.12	48.98
LocalMode	47.62	50.64	47.57	49.24	54.33	49.46	47.50	47.40
LocalSTD	25.72	27.75	25.83	29.22	34.74	29.55	25.48	25.53
LocalVariance	21.72	23.40	21.74	25.55	31.15	25.80	21.49	21.52

Table 4: Frequency of Patterns for Grass Texture.

	THL	MHL	BHL	LVL	MVL	RVL	LD	RD
Original	19.60	24.93	19.42	20.57	27.97	20.62	21.18	23.31
LocalMax	36.85	41.34	36.83	37.38	42.43	37.35	34.73	35.78
LocalMin	30.28	35.30	30.31	30.73	36.26	30.71	28.14	28.87
LocalMean	35.63	38.99	35.54	36.19	40.35	36.23	33.80	35.43
LocalMedian	35.57	38.94	35.46	36.19	40.54	36.33	33.67	35.42
LocalMode	22.92	27.84	22.90	23.39	28.74	23.37	21.75	22.34
LocalSTD	17.23	24.53	17.45	17.87	26.03	17.77	20.49	21.38
LocalVariance	13.20	19.78	13.36	13.80	21.32	13.76	15.97	16.91

3. Conclusions

From the Table 1 to Table 4, it is evident that the percentage of occurrences of all the simple patterns show a decreasing order on the binary images obtained from the preprocessing methods Local Max, Local Minimum, Local Mean, Local Median, Local Mode, Local standard deviation and Local Variance. The percentage of occurrence of the patterns are more are less same in the local mean and local median because of their physical and mathematical representation. One more important conclusion to be highlighted is that if a particular pattern P_i's percentage of occurrences is high in any of the preprocessed method, then the same trend is visible in all other preprocessed methods. From this the present paper concludes that whatever local preprocessing step is adopted for ensuring the quality of image, it has no effect on percentage of occurrence of simple patterns for classification or characterization of textures. And the relative percentage factor of occurrence of patterns is same irrespective of application of preprocessing.

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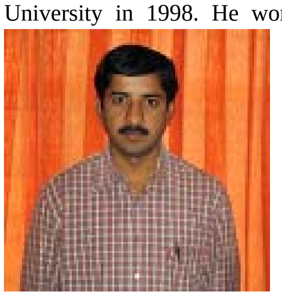

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