A Measure of Texture Directionality

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Abstract: Determining the directionality (i.e., orientedness) of textures is considered here. The work has three major components. The first component is a new method that indicates if a texture is directional or not. The new method considers both local and global aspects of a texture's directionality. Local pixel intensity differences provide most of the local aspect. A frequency domain analysis provides most of the global aspect. The second component is a comparison study (based on the complete set of Brodatz textures) of the method versus the known, competing methods for determining texture directionality. The third component is a user study of the method's utility.

1 INTRODUCTION

Image texture, while hard to well-define, involves some local order repeating over a larger area (Hawkins, 1970). In addition to having inherent features such as the size and degree of regularity in repetition, some textures also have orientation or other inherent features. Texture features have been used extensively in a variety of computer vision and pattern recognition applications. For example, Shiranita et al. have used texture features to determine the quality of meat (Shiranita et al., 1998). Gorkani and Picard have used texture orientation to detect images of urban areas (Gorkani and Picard, 1994). Mudigonda et al. have used texture features for detecting tissue masses in mammograms (Mudigonda et al., 2001). Texture features have also been extensively used to retrieve matching images from large image databases (Smith and Chang, 1996)(Saha et al., 2004)(Kekre et al., 2010).

Research has shown that certain characteristics of textures are readily perceived by human and animal vision. For example, studies (Hubel and Wiesel, 1968)(Blake and Holopigan, 1985) have found that the visual cortex of monkeys includes numerous detectors sensitive to orientation of structures in the visual field. Textures also help in visually differentiating surfaces (Beck, 1982)(Nothdurft, 1985). In addition, orientations within textures offer texture segregation cues to the visual system (Nothdurft, 1990)(Nothdurft, 1991). Additionally, Ware and Knight (Ware and Knight, 1992) have performed a user study that suggested that humans perceive there to be a number of visual characteristics of textures, such as regularity, size, and orientation.

In this paper, our focus is on determining if a texture is directional and on the use of directional textures. Directionality may be a useful feature for vision and pattern recognition since it would allow for differentiating between (i.e., classifying) textures. It may also be useful in multimedia, visualization and graphics applications. To support using texture directionality as a texture discriminator, a new measure that can determine the directionality status for a texture is introduced and validated here. We also present the first comparison study of texture directionality measures– that study includes comparison of the new measure against the existing measures, using user sentiment as a baseline.

The rest of the paper is organized as follows. Section 2 briefly discusses related work. Section 3 presents the new texture directionality measure. Section 4 presents the comparison of the directionality measures. Section 5 describes the user study. Section 6 analyzes the results, and Section 7 provides the conclusion and future work.

2 BACKGROUND

A number of frameworks for computing various types of texture measures have been reported (e.g., (Haralick, 1979)). In addition, some applications have used such measures. For example, Chetverikov has mea-

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sured texture regularity using a gray-level difference histogram feature (Chetverikov., 1984) and later used the measure in applications such as structural defect detection (Chetverikov and Hanbury, 2002). Cao et al. have derived a texture sharpness measure that is used in quantifying sharpness of digital images (Cao et al., 2009).

Our focus here is directional textures, so next we discuss previous work on texture directionality.

2.1 Textures and Directionality

Tamura et al. (Tamura et al., 1978) conducted an early study on the role of textures in human perception. They also introduced texture measures based on spatial intensity variation, one of which aimed at estimating overall directionality in an image. Their directionality measure was based on the sharpness of peaks in a histogram of high magnitude gradient pixels. The gradient values were estimated using mask-based horizontal and vertical directional difference estimates at each pixel. If a pixel's gradient magnitude was above a threshold, it was considered to be high magnitude. They also reported user studies that considered the correlation between human perception and their measures. The studies used 16 (of the 111) Brodatz image archive textures of various types. All possible combinations of pairs of these 16 images were shown to the participants, who then identified one texture from each pair that best exhibited the directionality characteristic. (Five other texture properties were also studied similarly.) Their study suggested that their directionality measure was highly correlated with the human responses.

Another texture directionality measure was defined by Picard and Gorkani (Picard and Gorkani, 1992). Their measure was based on a steerable pyramid defined with steerable filters like the ones described by Freeman and Adelson (Freeman and Adelson, 1991). Picard and Gorkani's pyramid had four levels, where the lowest level was the actual texture. At each level, the steerable filters were used to compute each pixel's dominant orientation and orientation "strength." Then, orientation histograms were constructed for each level based on the orientation strength values. After smoothing, the histogram peaks were found. Next, the orientation histograms for each level were combined. Finally, the measure of texture directionality was computed from this combination. Picard and Gorkani applied their measure to all 111 Brodatz textures and subsequently validated the measure via user study on the same textures.

Abbadeni (Abbadeni, 2000) and colleagues (Abbadeni et al., 2000) have proposed a measure of texture directionality based on a variance statistic, the auto-covariance function g. g expresses the covariance between the original image and a shifted version of that image, as shown in Eqn. 1:

$$g(\delta_i,\delta_j) = \frac{1}{c_{ij}} \sum_{i=0}^{n_c-\delta_i-1} \sum_{j=0}^{n_r-\delta_j-1} I(i,j)\, I(i+\delta_i, j+\delta_j), \tag{1}$$

where n_c and n_r are the number of columns and rows in the image I, respectively, the δ terms represent shifts, $0 \leq \delta_i \leq n_c - 1$ and $0 \leq \delta_j \leq n_r - 1$, and $c_{ij} = (n_c - \delta_i)(n_r - \delta_j)$. The approach found the gradient of the auto-covariance at each pixel. The pixels whose gradient exceeded a threshold t were considered to be oriented. In addition, if a sufficient number of pixels were considered to be oriented, then the image was considered to be a texture with a dominant orientation, denoted by Θ_d, and a directionality value N_{Θ_d}, defined as shown in Eqn. 2:

$$N_{\Theta_d} = \frac{\sum_{i=0}^{n_c-1} \sum_{j=0}^{n_r-1} \Theta_d(i,j)}{(n_c * n_r) - N_{\Theta_{nd}}}, \tag{2}$$

where $N_{\Theta_{nd}}$ is the number of non-oriented pixels. Abbadeni also performed a user study to validate the measure.

Hagh-Shenas and Interrante (Hagh-Shenas and Interrante, 2005) have also described a texture directionality measure. It is based on the Discrete Fourier Transform (DFT). It reduced DFT aliasing artifacts by applying a Hanning window to the original texture and then applying DFT on the Hanning-modified texture. Next, the DFT output was Gaussian-smoothed and converted into polar coordinates. The 180°-range of frequency values in the polar coordinates were divided into 18 equal intervals (through the DC point). Each interval was also radially divided by 64 circles, generating, in all, 18x64 locations. The values at these locations were stored in an 18x64 matrix called the Discrete Fourier Polar Coordinates Matrix (DFPM). Using the DFPM, a directionality measure, D_H, was computed, as shown in Eqn. 3:

$$D_H = \frac{\sum_{i=1}^{n} (M(i) - f(i))}{n * M(i)}, \tag{3}$$

where *f(i)* is the sum of the i^{th} column in the DFPM, $M(i)$ is the maximum value in that column, and n=64 columns.

Sikora et al. (Sikora, 2001) and Wu et al. (Wu et al., 1999) have used Gabor filter banks with scale and orientation sensitive filters to design texture features. These features were used to measure a concept related to directionality, the structuredness, of an image. Manjunath et al. (Manjunath et al., 2001) have also described texture descriptors that incorporate directional features for sub-regions of a texture. The set of features over all the sub-images were then used to formulate a feature vector for image indexing and retrieval. Directionality of the texture itself was not computed; hence, the texture is not classified as directional or non-directional.

Lastly, it should be noted that Healey and Enns (Healey and Enns, 1999) have presented an overview of the development of understandings and applications of texture in computer vision, graphics and visualization.

3 NEW TEXTURE DIRECTIONALITY MEASURE

A focus of our work is determining if a texture sample is directional. In this section, we describe the processing steps for our texture directional determination scheme. Our scheme considers both local and global aspects of directionality, which is one difference from most prior work.

The scheme acts as a measure that indicates if a texture is directional or non-directional. It examines directional intensity variations in texture as an initial step, then does a frequency domain analysis of the texture. This examination of intensity variation along predefined directions is aimed at identifying the more certain highly directional and highly non-directional textures first. Frequency domain analysis of the remaining textures provides more information on the texture directionality.

Computing the measure consists of applying the following steps to the texture sample.

Step 1. Compute pixel intensity differences along the 0, 45, 90 and 135 degree directions (from the horizontal) using a 3x3 neighborhood mask on each pixel of the texture.

Step 2. Compute the mean pixel intensity differences along each direction.

Step 3. Compute the max and min pixel intensity differences.

Step 4. Classify the texture as highly directional, highly non-directional, or possibly directional, using the following rules. If the difference, d, between the max and min pixel intensity differences is greater than a threshold t_1, classify the texture as highly directional. If d is greater than another threshold t_2, then classify the texture as highly non-directional (we use $t_1 > t_2$). Classify all textures with $t_2 \leq d \leq t_1$ as possibly directional. They need to be investigated further. (Note: The local intensity variation approach taken here is similar to the local binary pattern (LBP) concept (Ojala et al., 2002). However, instead of using the variation as a texture *discrimination* measure like LBP does, we compute a global orientation measure for the texture.)

Step 5. Stop if the texture was classified as highly directional or highly non-directional. Otherwise, proceed to Steps 5a, 5b, and 5c:

Step 5a. Apply a Fourier transform. (Our approach uses the Fourier tranform to assess geometric characteristics within a texture.)

Step 5b. Apply a Hough line transform to the output of Step 5a to identify existence of lines. The Hough transform is used to find structures in the Fourier transformed texture. Presence of linear-like structure in the Fourier transformed texture may indicate that the texture is oriented. The Hough line transform uses the line formulation shown in Eqn. 4:

$$xcos\theta + ysin\theta = \rho. \tag{4}$$

Eqn. 4 specifies a line passing through (x, y) that is perpendicular to the line from the origin to (ρ, θ) in polar space. For each point (x, y) on that line, ρ and θ are constant. The set of possible lines passing through (x, y) is obtained by solving for ρ and θ. An accumulator counts the number of times each (ρ, θ) combination describes a credible line passing through a pixel. Points that are collinear yield higher counts for the (ρ, θ) parameters describing their common line. Any time the accumulator count is high (we use 90 for our textures, which are size 128x128), we hypothesize such a line is present.

Step 5c. If one or many lines exist in the output of Step 5b, then classify the texture as a highly directional texture.

We use Hough processing after the Fourier step to allow some textures with disconnected directional components to be identified as directional (e.g., texture D102 from the Brodatz image archive); the local pixel difference method does not deal well with disconnected directional components. Furthermore, our approach also allows textures with multiple dominant directions to be detected as directional. Figure 1 shows such a texture, D102, with multiple dominant directions. Figure 2 shows the Fourier transformation of texture D102. The presence of straight lines in Figure 2 indicates that texture D102 is directional.

Since most prior texture directionality measures have been based on a local texture model, they may ignore some global aspects of texture directionality that could be utilized in human visual perception. Our measure, however, considers both local and global texture directionality (via its use of local pixel difference and Fourier and Hough steps). One limitation is that our measure only reports if the texture is oriented

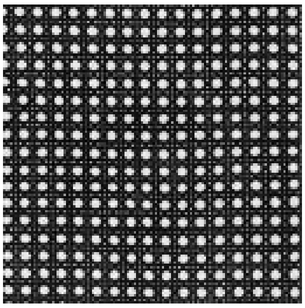


Figure 1: D102.

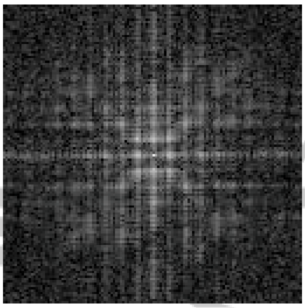


Figure 2: Fourier transform of D102.

or not; it does not report direction (i.e., the angle of texture's orientation). We hope to address this limitation in future work.

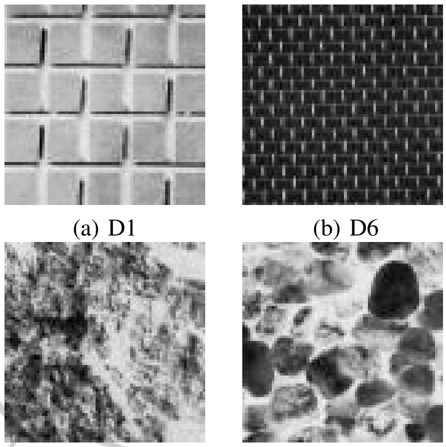
4 COMPARISON OF TEXTURE DIRECTIONALITY MEASURES

We next report on our comparison study. It evaluates our directionality measure versus the four prior measures. In our comparison, we applied all the measures to the complete archive of 111 Brodatz textures. Previously, only Picard and Gorkani have reported a complete test, for their measure alone, on the entire Brodatz archive. Thus, the report here represents the first comprehensive comparison of the existing and new texture directionality measures.

Table 1: List of consistently-classified textures.

Directional	**Non-directional**
D1,D6,D11,D15,D18,D20, D24,D25,D26,D34,D36,D37, D47,D49,D50,D51,D52,D53, D55,D56,D65,D68,D70,D72, D76,D77,D78,D79,D83,D94, D95,D96,D105,D106	D2,D23,D28,D30, D32,D33,D40,D41, D54,D60,D62,D63, D66,D67,D75,D88, D89,D91,D100, D109,D111

For the Abbadeni measure, we had to make two assumptions due to incomplete information in their paper: (1) the threshold for whether a pixel is oriented, and (2) the criterion to determine a dominant orientation. We determined these thresholds for our work here as follows. (1) We have used the average orientation of all the pixels in the texture as the threshold to determine which *pixels* are oriented. (2) If more than half the texture's pixels are oriented then we consider that *texture* to have a dominant orientation. We label textures with a dominant orientation as directional textures.



(a) D1 (b) D6

(c) D2 (d) D23

Figure 3: Sample textures that are consistently- classified (D1 and D6 directional; D2 and D23 non- directional).

Table 1 lists textures from the Brodatz archive that were classified consistently by the directionality measures (i.e., the table shows the texture images for which the five measures were in agreement). Table 2 lists the Brodatz texture images for which the five measures disagreed, with N and D used to denote classification as non-directional and directional, respectively. We have computed the Pearson correlation coefficient (Jackson, 2009) for only these inconsistencies to measure the correlation among all measures. The Pearson correlation coefficient here tests the null hypothesis that there is no significant correlation in data. Table 3 shows the correlation matrix, using a 95% level of confidence value. We discovered that our measure and Hagh-Shenas's measure had the best correlation. The second best correlation was our measure with Picard and Gorkani's measure.

5 USER STUDY

A subset of the Brodatz textures was used in our user study, which we describe next. We consider the study's results as a ground truth to compare the texture directionality measures.

The study's protocol, which was approved by the

Table 2: Classification of remaining Brodatz textures by measure (T= Tamura et al., H=Hagh-Shenas and Interrante, P=Picard and Gorkani, A=Abbadeni et al., and M=My measure), with N indicating a non-directional classification and a D indicating a directional one.

ID	T	H	P	A	M	ID	T	H	P	A	M
D3	D	D	D	N	D	D59	N	N	D	D	N
D4	N	D	N	N	N	D61	N	N	N	D	N
D5	N	N	N	D	N	D64	D	D	D	N	D
D7	D	D	D	D	N	D69	D	N	D	D	N
D8	N	N	D	D	N	D71	N	D	N	N	N
D9	N	D	N	N	N	D73	N	N	N	D	N
D10	N	D	D	N	N	D74	D	N	N	N	N
D12	D	D	D	D	N	D80	N	N	D	N	N
D13	D	N	D	D	N	D81	N	D	D	N	N
D14	D	N	D	D	N	D82	N	D	D	N	N
D16	N	D	D	D	N	D84	N	N	D	D	N
D17	N	D	D	D	N	D85	N	D	D	D	D
D19	N	N	N	D	N	D86	N	D	N	D	N
D21	N	D	D	D	D	D87	N	N	D	N	N
D22	N	D	D	D	D	D90	N	N	N	D	N
D27	N	N	N	D	N	D92	N	D	N	D	N
D29	N	N	N	D	N	D93	D	N	D	N	N
D31	D	N	N	N	N	D97	N	N	D	D	D
D35	D	D	D	N	D	D98	N	N	D	N	N
D38	N	N	D	D	N	D99	N	N	N	N	D
D39	N	N	N	D	N	D101	N	D	D	N	D
D42	N	N	D	D	N	D102	N	D	D	D	D
D43	N	N	D	D	N	D103	D	D	D	N	N
D44	N	D	D	D	N	D104	D	D	D	N	N
D45	N	N	D	N	N	D107	N	N	D	N	N
D46	D	N	D	D	D	D108	N	N	D	D	N
D48	N	N	D	D	N	D110	N	N	N	D	N
D57	N	D	N	N	N	D112	N	N	N	D	N
D58	N	N	N	D	N						

institution's Human Subjects Committee, involved first providing a 2-3 minute overview about textures to each participant. All participants considered the same set of questions, with the study administered in a computerized form. Participants were isolated from each other.

5.1 Subjects

Twenty two individuals participated in the study. Twelve were atmospheric science graduate students and ten were environmental scientists.

5.2 User Study Task

In the study, participants were asked to perform a task, which we describe next. Each participant completed classification of 15 Brodatz textures (shown in Figure 4) into one of three classes: highly directional, highly non-directional, and somewhat directional. Like Tamura, we selected these 15 at random, 5 per classification (from our measure). We used a small subset rather than the complete set of Brodatz textures to avoid user fatigue.

The overall results from the task are shown in Table 4, where highly non-directional, highly directional, and somewhat directional textures are denoted by 0, 2, and 1, respectively. The rows of the table list individual textures. The columns of the table list participant classifications.

Comparisons of classifications produced by the user task against those from the existing directionality measures are reported in Table 5. In the table, the *highly directional* and *somewhat directional* classes from the user task are grouped together. N and ND represent directional and non-directional, respectively. Our method concurs with the user study results 93% of the time. We believe that this is due to global directionality being addressed by our method as well as in human vision.

Table 3: Pearson Correlation Coefficient for inconsistent classification.

	T	H	P	A	M
T	1				
H	0.17379	1			
P	0.24871	0.25472	1		
A	-0.21738	-0.27275	-0.05432	1	
M	0.20521	0.34405	0.28949	-0.03257	1

Table 4: User classification of the textures.

D9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D14	0	0	0	0	1	0	1	0	0	0	1	1	1	0	0	0	0	0	1	0	0	1
D21	2	2	2	2	2	2	2	2	1	2	2	2	2	2	2	1	1	2	2	2	2	2
D25	2	2	2	2	1	1	0	2	2	2	2	2	2	2	2	2	2	2	1	1	2	0
D31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D34	2	2	2	2	1	1	2	1	1	1	1	2	2	1	1	1	1	1	1	1	2	2
D49	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
D53	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	2	2	2	2	2	2
D58	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
D60	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D65	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
D75	0	0	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	1	0	0
D78	0	1	1	1	2	0	0	1	1	0	1	1	1	1	1	0	1	1	2	1	1	0
D86	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
D97	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1

6 ANALYSIS

Next, we present a comparison of the directionality measures performance. We do so using a comparison

Table 5: Task 1 classifications vs. the classifications from the five measures.

	D9	**D14**	**D21**	**D25**	**D31**	**D34**	**D49**	**D53**	**D58**	**D60**	**D65**	**D75**	**D78**	**D86**	**D97**
User Study	ND	ND	D	D	ND	D	D	D	ND	ND	D	ND	D	ND	ND
Our Metric	ND	ND	D	D	ND	D	D	D	ND	ND	D	ND	D	ND	D
Abbadeni	ND	D	D	D	ND	D	D	D	D	ND	D	ND	D	D	D
Picard and Gorkani	ND	D	D	D	ND	D	D	D	ND	ND	D	ND	D	ND	D
Hagh-Shenas	D	ND	D	D	ND	D	D	D	ND	ND	D	ND	D	D	ND
Tamura	ND	D	ND	D	D	D	D	D	ND	ND	D	ND	D	ND	ND

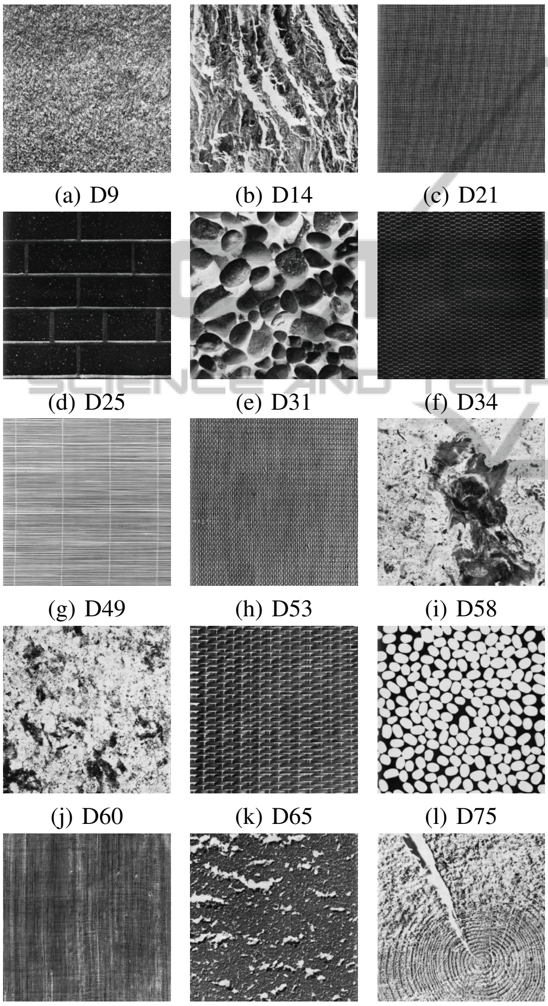

(a) D9 (b) D14 (c) D21
(d) D25 (e) D31 (f) D34
(g) D49 (h) D53 (i) D58
(j) D60 (k) D65 (l) D75
(m) D78 (n) D86 (o) D97

Figure 4: The Brodatz textures used in Task 1.

of classifiers mode, where the user study result is used as the ground truth set and each measure is used as a classifier. Classifier performance is considered here using precision versus recall. Precision is the ratio of the number of correct classifications to the total number of classifications. Recall is the ratio of the number of correct classifications to the total number of correct classifications.

Figure 5 shows the plot of precision versus recall for all texture orientation measures using the user study results as ground truth. The figure suggests that our measure has high precision at all recall levels, in particular that our new method's precision exceeds that of the existing measures.

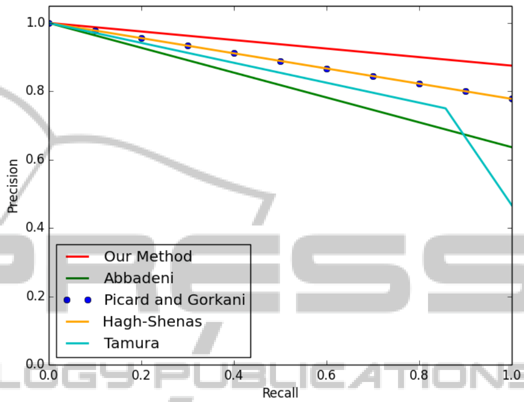


Figure 5: Precision versus recall comparison of texture orientation measures.

7 CONCLUSIONS

In this paper we have presented a new texture directionality measure and validated the measure with user studies. The measure allows determination of suitable directional textures. We have also compared, for the first time, the existing texture orientation measures using an identical set of images. In the future, we hope to study other aspects of texture orientedness, such as allowing for determination of which direction is a dominant one in a directed texture.

REFERENCES

Abbadeni, N. (2000). Autocovariance-based perceptual textural features corresponding to human visual perception. In *Proc., Int'l Conf. on Pattern Recognition '00*, volume 3, pages 901–904.

Abbadeni, N., Zhou, D., and Wang, S. (2000). Computational measures corresponding to perceptual textural features. In *Proc., Int'l Conf. on Image Processing '00*, volume 3, pages 897–900.

Beck, J. (1982). *Textural Segmentation, in Organization and Representation in Perception*. Hillsdale, NY: Erlbaum.

Blake, R. and Holopigan, K. (1985). Orientation selectivity in cats and humans assessed by masking. *Vision Research*, 25(10):1459–1467.

Cao, F., Guichard, F., and Hornung, H. (2009). Measuring texture sharpness of a digital camera.

Chetverikov., D. (1984). Measuring the degree of texture regularity. in proc. international conf. on pattern recognition. In *Proc., International Conf. on Pattern Recognition*, pages 80–82.

Chetverikov, D. and Hanbury, A. (2002). Finding defects in texture using regularity and local orientation. *Pattern Recognition*, 35(10):2165–2180.

Freeman, W. and Adelson, E. (1991). The design and use of steerable filters. *IEEE Trans. Pattern Anal. and Machine Intel.*, 13(9):891–906.

Gorkani, M. and Picard, R. (1994). Texture orientation for sorting photos "at a glance". In *Pattern Recognition, 1994. Vol. 1 - Conference A: Computer Vision amp; Image Processing., Proceedings of the 12th IAPR International Conference on*, volume 1, pages 459–464 vol.1.

Hagh-Shenas, H. and Interrante, V. (2005). A closer look at texture metrics. In *Proc., 2nd Symp. on Applied Perception in Graphics and Vis. (APGV '05)*, pages 176–176.

Haralick, R. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*, 67(5):786–804.

Hawkins, J. K. (1970). *Picture Processing and Psychopictorics*. Academic Press, New York, NY, USA, as cited by W. K. Pratt, *Digital Image Processing 2nd Ed.*, 1991, Wiley.

Healey, C. and Enns, J. (1999). Large datasets at a glance: Combining textures and colors in scientific visualization. *IEEE Trans. Vis. and Computer Graphics*, 5(2):145–167.

Hubel, D. and Wiesel, T. (1968). Receptive fields and functional architecture of monkey striate cortex. *Physiology*, 195:215–243.

Jackson, S. L. (2009). *Research Methods and Statistics : A Critical Thinking Approach*. Wadsworth Cengage Learning, Belmont, CA.

Kekre, H., Thepade, S. D., Jain, J., and Agrawal, N. (2010). Article:iris recognition using texture features extracted from haarlet pyramid. *International Journal of Computer Applications*, 11(12):1–5. Published By Foundation of Computer Science.

Manjunath, B., Ohm, J.-R., Vasudevan, V., and Yamada, A. (2001). Color and texture descriptors. *Circuits and Systems for Video Technology, IEEE Transactions on*, 11(6):703–715.

Mudigonda, N. R., Rangayyan, R. M., and Desautels, J. L. (2001). Detection of breast masses in mammograms by density slicing and texture flow-field analysis. *Medical Imaging, IEEE Transactions on*, 20(12):1215–1227.

Nothdurft, C. (1985). Sensitivity for structure gradient in texture discrimination tasks. *Vision Research*, 25:1957–1968.

Nothdurft, C. (1990). Texton segregation by associated differences in global and local illuminance distribution. In *Proc., R Soc Lond Ser B Biol Sci*, pages 295–320.

Nothdurft, C. (1991). Texture segmentation and pop-out from orientation contrast. *Vision Research*, 31:1073–1078.

Ojala, T., Pietikainen, M., and Maenpaa, T. (2002). Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24(7):971–987.

Picard, R. and Gorkani, M. (1992). Finding perceptually dominant orientations in natural textures. *Spatial Vision*, 8(2):221–253.

Saha, S., Das, A., and Chanda, B. (2004). Cbir using perception based texture and colour measures. In *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, volume 2, pages 985–988 Vol.2.

Shiranita, K., Miyajima, T., and Takiyama, R. (1998). Determination of meat quality by texture analysis. *Pattern Recognition Letters*, 19(14):1319 – 1324.

Sikora, T. (2001). The mpeg-7 visual standard for content description-an overview. *Circuits and Systems for Video Technology, IEEE Transactions on*, 11(6):696–702.

Smith, J. and Chang, S.-F. (1996). Automated binary texture feature sets for image retrieval. In *Acoustics, Speech, and Signal Processing, 1996. ICASSP-96. Conference Proceedings., 1996 IEEE International Conference on*, volume 4, pages 2239–2242 vol. 4.

Tamura, H., Mori, S., and Yamawaki, T. (1978). Textural features corresponding to visual perception. *IEEE Trans. Sys., Man and Cybernetics*, 8(6):460–473.

Ware, C. and Knight, W. (1992). Orderable dimensions of visual texture for data display: Orientation, size, and contrast. In *Proc., ACM Conf. on Human Factors in Computing Sys. '92*, pages 203–209.

Wu, P., Manjunanth, B., Newsam, S., and Shin, H. (1999). A texture descriptor for image retrieval and browsing. In *Content-Based Access of Image and Video Libraries, 1999. (CBAIVL '99) Proceedings. IEEE Workshop on*, pages 3–7.