1. Introduction to Texture Analysis

A texture pattern is a grainy, fibrous, or woven pattern as opposed to a constant pattern. It is composed of a large number of simple primitive elements or patterns [Ballard and Brown, 1982, pp. 169]. Usually no two patterns of the texture field are identical. The extent to which the simple texture primitive patterns differ and the manner in which they are spaced determines the texture pattern. A texture primitive is a basic texture element that occurs in different positions, deformations, or orientations inside a texture field. The process by which the pattern is repeated may by deterministic or stochastic. In most cases the pattern that is being repeated is not identical from place to place. The local pattern has similar properties from place to place. A pattern class is being repeated where all examples are perceived as equivalent. Also the spatial placement of the pattern is not exact. There may be random phase shifts in the placement rules. In addition, the matrix underlying the pattern may be stretched or twisted as occurs in fabric examples. Texture patterns commonly occur in outdoor scenes. Common examples grass images, tree images, different types of vegetation, row crops, and residential areas. Many image problems in medical images are characterized by texture patterns. In manufacturing the surface properties of materials are often characterized by texture patterns.

Texture is difficult to define and people do not bother to try and define texture [Rao, 1990]. The problem is to develop a symbolic representation for texture and determine computer methods for associating images of texture patterns with their symbolic descriptions. At the present time there does not exist a commonly accepted set of descriptive terms for texture patterns. This means symbolic descriptions that may be used in analysis methods do not generalize.

Image resolution is a factor in texture patterns [Ballard and Brown, 1982, pp. 170]. Suppose one has a fixed resolution corresponding to a window that one extracts from the image. As the window gets smaller, fewer texture primitives are in the field until finally the window is so small that the primitive does not fit within the window. As the window gets larger, at some point the texture primitive becomes indistinct or blurry and forms a continuous gray-tone. There is then a range of resolutions at which the texture patterns is discerned. This same observation applies to discrete images. If one images a forest at a coarse resolution, say 30 meter by 30 meters, then the image will be a continuous tone or color. As the resolution increases a texture pattern of the trees appears. As the resolution increases even more the texture pattern changes to the leaf pattern and not the tree pattern.

Figure 1. Image of grass in a field (Taken from National Agricultural Library)

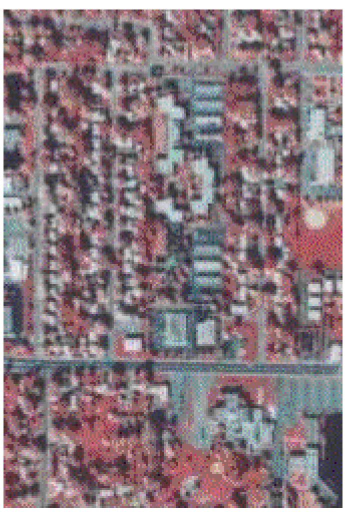


Figure 2. Aerial Image of an Urban Area (Taken from Minnesota Dept. of Natural Resources)

Figure 3. Image of Cork

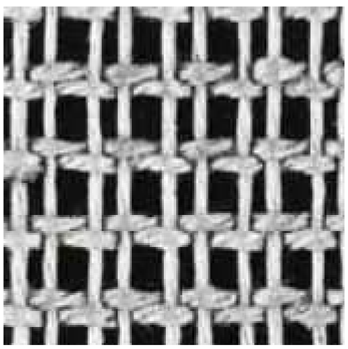


Figure 4. Image of French Canvas

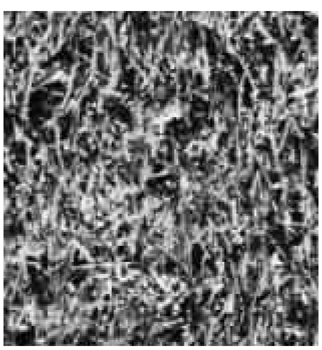
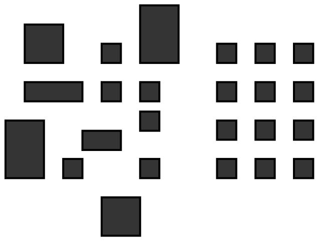


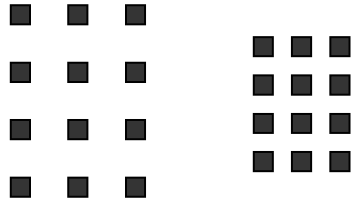
Figure 5. Image of Grass. taken from brodatz

The following are some descriptive terms that have been applied to texture patterns [Levine, 1985, pp. 423, Haralick, 1979, Tamura, Mori, Yamawaki, 1978].
fine and coarse
directional
smooth or rough
granulation
random, regular or irregular
linear
mottled
irregular or regular
hummocky
density
phase

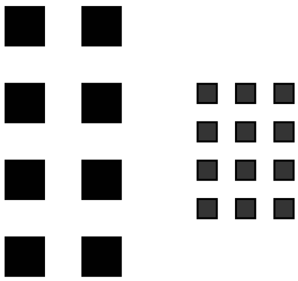
The term coarse relates to the size and spacing of the primitive texture element. The bigger the element and the wider the spacing between elements then the coarser the texture. When two textures differ only in scale the magnified one is coarser.
The directional term involves the primitive element placement as it refers to orientation of the element. This term refers to the orientation of the texture patterns.
The term linear refers the texture primitive shape and placement having a line like pattern.
The term rough or smooth relates to tactile surfaces. It relates to gray shades and perceived roughness.
The term regular and irregular refers to the variation in the primitive shape and placement rule.
Density refers to the spacing size between the primitive texture elements.
Phase refers to the variation in the location of the primitive element placement rules but not the spacing between them.



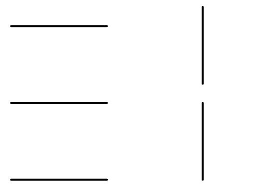
irregular and
regular



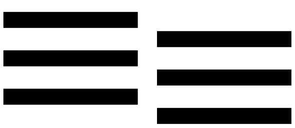
density



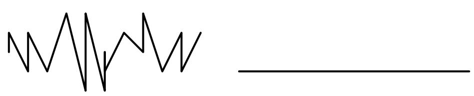
coarse and fine
frequency



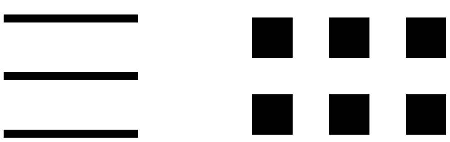
directionality



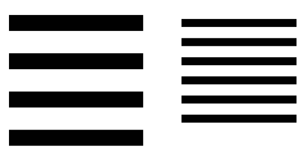
phase



rough and smooth, the
line height represents
the gray-level
variation



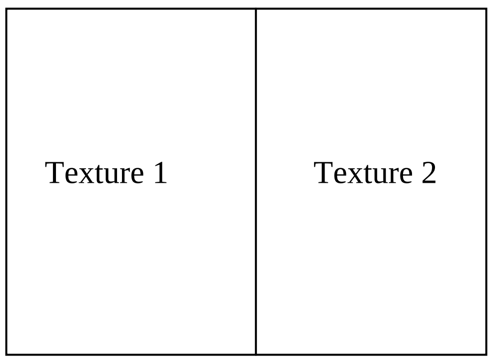
linear and nonlinear



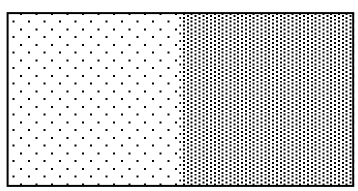
frequency

1.1 Perceptual Levels in Texture Discrimination

There are different levels of texture discrimination. One level is called spontaneous discrimination or preattentive texture discrimination [Rao, 1990, pp. 4]. This perception does not involve high level processing in the brain. Deliberate discrimination requires cognitive processes of the brain. With preattentive texture discrimination, humans make distinctions quickly between texture patterns. A common format for these experiments is to present two texture patterns in one image.



The following figure gives two texture patterns that humans spontaneously can distinguish.



One can study texture on several levels. One is the statistical level. A conjecture is that one can discriminate textures based upon statistical properties. There is a question as to the order of the probabilities that one must consider. A conjecture is that textures with identical first and second order probabilities are not distinguishable by humans.

1.2 Statistical Analysis of Texture Patterns

Assume g(x,y) is a random variable with a probability of having a certain value g(x,y)=k. Then p(k)=P{g=k} is the probability that g has value k. If the gray-level values are between 0, 1, ..., L-1, then $\sum_{k=0}^{L-1} P\{g=k\} = \sum_{k=0}^{L-1} p(k) = 1$. This is the first-order probability function. This is also called the histogram h(k) when one estimates p(k) from available image data. The cumulative probability function is denoted by F(k). It is related by the following equations to p(k) the probability function. In the continuous case $F(k) = \int_{-\infty}^{k} p(k)dk$ and $p(k) = \frac{dF}{dk}$. In the discrete case, $F(k)=\sum_{i=0}^{k} p(i)$. F(k) is the probability that $g(x,y) = i \le k$ or $f(k) = P\{g \le k\}$.

The set of all the random variables over the pixels of the image forms a random process. A random process is stationary if the statistics at each pixel are the same [Papoulis, 1965, pp.300]. A random process is ergodic if time averages are the same as ensemble averages [Papoulis, 1965, pp.327]. If one assumes that the random variable is ergodic then the spatial computations over (x,y) may be used to compute F(k) and p(k). If there are L gray-levels then L parameters must be estimated to determine p(i). For this reason one often extracts measures from p(i).

One can also discuss joint probabilities. Recall that p(k) is the probability that g has value k. Let $u_1 = (x_1, y_1)$ be a point in the image. Then $p(k) = P(g(u_1) = k_1)$ that we write as $p(k) = p_{u_1}(k_1)$. One may then consider two points $u_1 = (x_1, y_1)$ and $u_2 = (x_2, y_2)$ with joint probabilities $p(k_1,k_2)=P\{(g(u_1)=k_1) \ \& \ (g(u_2)=k_2)\}$ which we write as $p_{u_1,u_2}(k_1,k_2)$. We may continue and consider n pixels to get $p(k_1,k_2,\ldots,k_n)=P\{(g(u_1)=k_1) \ \& \ (g(u_2)=k_2) \ \ldots \& \ (g(u_n)=k_n)\}$ that we write as $p_{u_1,u_2,\ldots u_n}(k_1,k_2,\ldots k_n)$. The points $u_1, u_2, \ldots, u_n$ define the sampling geometry of the image for the statistical analysis.

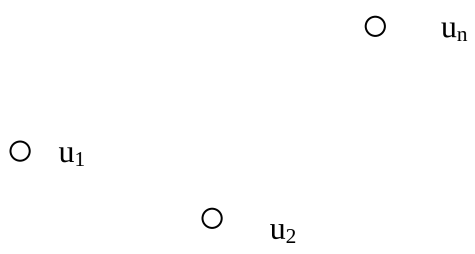


Figure 6. Sampling Geometry

Let $u = \{u_1, u_2, \ldots, u_n\}$ define a sampling geometry. Let d be a translation distance vector $d = (d_1, d_2)$ for two-dimensional images. Let $u = \{u_1, u_2, ..., u_n\}$ and $u + d = \{u_1 + d, u_2 + d, ..., u_n + d\}$. Then we write $p_u(k)$ where $k = (k_1, k_2, \ldots, k_n)$. Let d be a translation vector. Then the process is translation stationary if $p_u(k) = p_{u+d}(k)$. We usually assume translation stationary and ergodic processes.

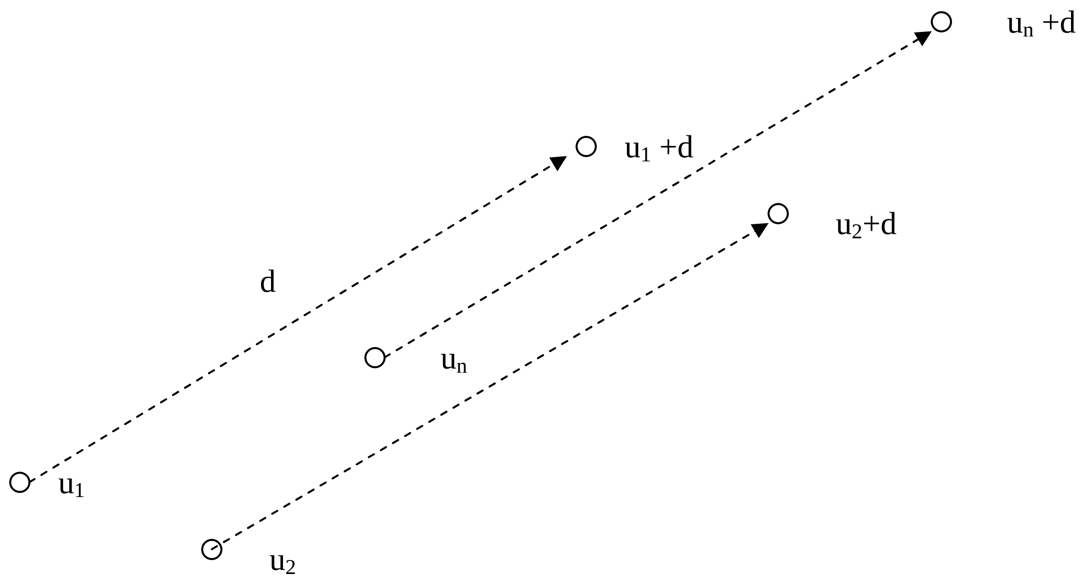


Figure 7. Translation of Vectors by d

Now one can consider generating texture patterns from images A and B and computing joint statistics from the two images so that we get the joint statistics $p^A{}_{u_1,u_2,\ldots u_n}(k_1,k_2,\ldots k_n)$ or just $p^A(k_1,k_2,\ldots k_n)$ from image A and $p^B(k_1,k_2,\ldots k_n)$ from image B. We say the texture patterns A and B can be statistically discriminated at level n if
$p^A(k_1,k_2,\ldots k_{n-1}) = p^B(k_1,k_2,\ldots k_{n-1})$ but
$p^A(k_1,k_2,\ldots k_n) \neq p^B(k_1,k_2,\ldots k_n)$.
A pertinent question is what is the smallest n such that no two textures can be discriminated by humans?

1.3 References

Ballard, D. B., and Brown, C. M. (1982). *Computer Vision*, Prentice Hall, Englewood Cliffs, N. J.

Brodatz, P. (1966). *Textures*, Dover Publications, Inc.

Haralick, R. M. (1979). “Statistical and Structural Approaches to Texture.” *Proceedings of IEEE*, Vol. 67, No. 5, May 1979.

Julesz, B. (1962). “Visual Pattern Discrimination.” *IRE Transactions on Information Theory*, Vol. 8, 1962, pp. 84-92.

Levine, M. D. (1985). *Vision in Man and Machine*, McGraw-Hill Book Company.

Rao, A. R. (1990). *A Taxonomy for Texture Description and Identification*, Springer-Verlag.

Tamura, H., Mori, S., and Yamawaki, T. (1978). “Textural Features Corresponding to Visual Perception.” *IEEETransactions on Systems, Man, and Cybernetics*, Vol. SMC-8, No. 6, June 1978, pp. 460-472.

Tomita, F., and Tsuji, S. (1990). *Computer Analysis of Visual Textures*, Kluwer Academic Publishers.

Zhu, S. C., Liu, X. W., and Wu, Y. N. (2000). “Exploring Texture Ensembles by Efficient Markov Chain Monte Carlo-Toward a Trichromancy Theory of Texture.” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 6, June 2000..