FREQUENCY MAGNITUDE AND IMAGES OF TEXTURE

Studies on Relationships to Human Preference

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Abstract. A relationship between spatial frequency magnitude and aesthetic preference for texture is established in this work. This paper examines the mean output of three frequency settings in terms of preference ratings for a bank of Gabor filters. Three studies were conducted and the correlations between aesthetic ratings and the mean output for the filter set to extract frequency content at the scale of 0.35 cycles/ pixel were robust. The correlations for the mean frequency magnitude of this filter remained significant when image identifiability was incorporated; suggesting that memory and association are not exclusively driving (aesthetic) preference. These results are consistent with findings reported by Albrecht and Geisler (1997), demonstrating that human beings are tuned to specific frequencies and orientations. Overall, the results reported in this paper begin to substantiate a claim that specific frequencies contained in images do play a significant role in human preference.

1. Goodness of Form - Prägnanz

Early in the last century the quality of a visual experience was approached by Gestalt psychologists through the analysis of ‘goodness’ of form, or *prägnanz*, which—in their opinion— was an important factor in perceptual experience (Beardslee et al., 1923; Kofka, 1922; Mowatt, 1940; Kohler, 1947). Perceptual “experience” was said to correspond to global properties of subjective simplicity, complexity and bilateral symmetry. Researchers did not believe whole figures could be understood by means of examining the local properties of those figures. Some images were thought to produce experiences of greater simplicity, order and regularity than others. Stimuli that are simple (contain adequate redundancy), symmetric (rotationally invariant) and familiar were considered “good”. However, a reliable description for judged simplicity was not determined and the relationship between symmetry and figural “goodness” (prägnanz) was not demonstrated. Symmetry proved only to be a tenable explanation and local asymmetry was not addressed (Garner 1962, 1970).

Despite later findings (Michael, 1953; Checkosky et al., 1973; Clement et al, 1970; Pomerantz et al, 1973a, 1973b, 1977, 1991), there was still doubt to what physiological mechanisms are responsible for 'goodness of form'. Both symmetry and simplicity were determined to be unsatisfactory means to understand what was responsible for prägnanz (Pomerantz, 1986). At that time, responses to specific physical measures were not considered. Nevertheless, recent study has shown that there is a measurable relationship between texture properties and aesthetic preferences (Schira, 2003).

Some characteristics of texture are recognizable by human perception and considerable effort has gone into identifying those characteristics (Amadasun et al., 1989; Argenti et al., 1990; Haralick et al., 1973; Haralick, 1979; Julesz, 1962, 1975, 1981, 1984). Such analysis is based upon the idea that an object's surface characteristics correspond directly with variations in intensity between any one element (pixel) extant within the two dimensional image of that object.

Texture is one of the characteristics used to identify objects or visual regions of interest in an object. It can be evaluated as fine, coarse, rippled or irregular and can essentially be described as the structural arrangement of a visual surface and the relationship that arrangement has with others surrounding it. Tone can be defined as the variation of the pixel gray values in a local area, and texture, the distribution of those gray (tone) values, or the repetition of a gray (tone) value. Hence, texture is described here to be the random or constant distribution of tonal elements within an image. It is the repetitive and or random distribution of those "elements" that are of interest in evaluating an image's texture-tone properties.

2. Texture Properties and Multi-channel Bandpass Filters

Models based on the human visual system have been implemented for textural analysis with varying degrees of success (Mitchell et al., 1992; Rao et al., 1993; Tamura et al., 1978). Multi-resolution bandpass filtering (Bovik et al., 1989, 1990; Coggins et al., 1985; Tan, 1992, 1990) called Gabor Filtering (Gabor, 1946) is based on multi-channel filter theory and has been used for purposes of texture analysis (Bovik et al., 1989, 1990; Ghosh et al., 1990; Jain et al., 1991) where dominant size and orientations of texture can be discriminated (DeValois, 1976).[1] Developed from early wave physics filter theory was derived from the hypothesis that the visual system uses a method not unlike Fourier (1822), where the retinal image is composed of an

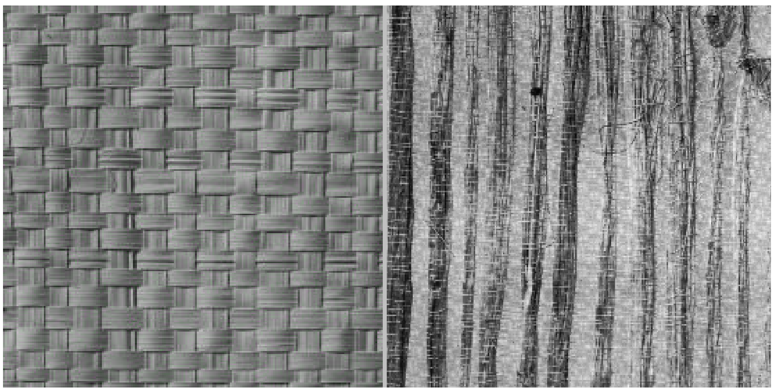
[1] Bandwidths (at ½ amplitude) varied from narrow to broad (0.7 to greater than 2 octaves). Orientation tuning varied from ± 4° to greater than ±50°. Nevertheless, at least 25% of the cells were narrowly tuned to only 0.7 to 1.2 octaves in spatial frequency and ± 4 to 10° in orientation.

array of light (Cugell et al., 1966; Hubel et al., 1959, 1962, 1968; Kuffler, 1953; Maffei et al., 1973). It was suspected that such an array activates individual channels tuned to different bands of spatial frequencies; that is, the human visual system decomposes the retinal image into a number of filtered images, each containing variation in intensity over a narrow frequency range and orientation (Albrecht et al., 2000; Malik et al., 1990). Later, it was found that mechanisms in the visual cortex of mammals are tuned to combinations of narrow range frequency and orientation (Albrecht et al, 1997). Following these findings, a relationship has been demonstrated between global magnitudes of spatial frequency and aesthetic preference for texture (Schira, 2002). The performances of specific frequency and orientation settings were not reported. This paper now examines the mean output of three frequency settings and their performance in terms of preference ratings.

3. Experiment Overview

SELECTION STUDY "S"

The purpose this study was to determine (select) a set of twenty stimuli that could be considered relatively un-recognizable from the starting set of 50 (see Methods). Since the participants would serve to scrutinize the actual "identifiability" of the stimuli, texture images considered to be identifiable were included. A texture considered identifiable is shown in Fig.1a and one that is non-identifiable in Fig.1b. This distinction is important to (the last) Study V, where identifiable stimuli are included.



(a) *(b)*

Figure 1. Images easy (*a*) and difficult (*b*) to identify (Brodatz 1956).

The images which had a higher incidence of identical "labels" by the judges, consequently received higher "identifiability" counts and were omitted from 'possible stimuli' list. Images receiving the lowest count on "identifiability" were added to the 'possible stimuli' list; to be used as stimuli in subsequent studies.

Twenty-six subjects participated in this study and were instructed to give a preference rating for the 50 stimuli. The same set was then re-presented and they were asked to identify each stimulus. If they could not either identify or guess the stimulus with less than three words they were to mark "don't know" in the space provided on the data sheet.

Results Study "S"

The correlation (*r*) between the preference ratings and Frequency settings 1M, 2M and 3M were -0.22, -0.36 and -0.55 respectively; shown in Table 1. Beyond the scope of these proceedings, mean and standard deviation of the preference ratings as well as the values of mean freq., 1M, 2M, 3M, for each image in all studies scatter-grams of the correlations obtained for this and all studies throughout this paper have been omitted.[2]

TABLE 1. Correlations (*r*) in Study "S" between preference ratings and mean frequency magnitudes.

Selection				
r	PrefS	1M	2M	3M
1M	-0.22	1		
2M	-0.38	0.41	1	
3M	-0.55	0.11	0.55	1

The critical value of correlation (*r*) for significance is 0.276; with degrees of freedom (*df*) = 49 for alpha (**a**) = 0.05; and 0.358 for alpha (**a**) = 0.01; indicating correlations for 2M and 3M are significant to large. The value of multiple correlation (*R*) was also significant at $R = 0.58$, $F\ (3, 46) = 7.78$, $p = 0.0003$.

Twenty "possible stimuli", to be used in subsequent studies, were selected from the 50 stimuli according to consistency based upon the mean and standard deviation of preference ratings across participants as well as their "identifiability" score. That is, those not discarded were considered sufficiently non-identifiable in the following study.

[2] Scattergrams are available through the author and will appear in future publication under review by Environment and Planning B: Planning and Design, Pion: London.

CONFIRMATION STUDY "C"

The purpose of this study was to determine the consistency of the relationship between preference for texture stimuli and the mean frequency output for the three settings 1M, 2M and 3M (See Methods) while controlling for variables of identifiability. Two tests were conducted; the first had 98 participants judging stimuli set C1 (see Fig.2); the second had 130 subjects judging set C2 (see Fig.3). Both sets had twenty stimuli and were identical except for the substitution of five stimuli in C2 to verify the consistency of the correlations found in test C1 for mean freq magnitudes of filters 1M, 2M and 3M (if significant) when the context changed.

Insert *Figure 2.* Stimuli shown to subjects in Study "C-1"

Insert *Figure 3.* Stimuli shown to subjects in Study "C-2"

Results Study "C"

Correlations for tests C1 and C2 are shown in Table 2. Significance is based upon crit.(r) = 0.444 (for df = 19, crit.(r) = at **a** = 0.05; crit.(r) = 0.561 at **a** = 0.01); indicating that correlations (-0.59 and -0.63) for filter 3M were largely significant and robust, whereas 1M (0.03 and -0.19) and 2M (-0.27 and -0.29) were not significant in either test. In test C1, multiple (R) = 0.60, F (3, 16) = 2.96, p = 0.0639; and in test C2 multiple (R) = 0.65, F (3, 16) = 3.90, p = 0.02. The lower than significant result for test C1 multiple correlation for the three filters is not surprising, given that single (r) for 1M and 2M was not significant. Nevertheless, this issue is trivial to the paper, since we are evaluating the individual performances of the filters. The performance of a bank of filters is evaluated in (Schira, 2002).

TABLE 2. Correlations (r) in Study "C" between preference ratings and mean frequency magnitudes.

Confirm1					Confirm2				
r	Pref1	1M	2M	3M	***r***	Pref2	1M	2M	3M
1M	0.03	1			1M	-0.19	1		
2M	-0.27	0.06	1		2M	-0.29	0.10	1	
3M	-0.59	0.11	0.54	1	3M	-0.63	0.07	0.48	1

Discussion

The results of test C2 are consistent with those of C1.With the exception of stimulus D019 and D006, mean frequency content taken with filter 3M increase as the mean preference ratings decrease.[3] With the exception of a few images such as D111 and D086, the stimuli most preferred and least preferred are fairly clear in terms of 3M magnitudes. Regardless of the change of context introduced by substituting stimuli in the second test, the correlations for 3M remained large.

VALIDATION STUDY "V"

The purpose of this study was to validate the significance of the correlations previously found, including the significance of the correlations in the initial "Selection" study. Images previously determined to be identifiable in the Selection Study (discarded from all three tests in Study "C") were included in this stimulus set. Therefore, the stimulus set included fifty-three stimuli that were both identifiable and non-identifiable. There were 62 participants.

Results Study "V"

Correlations between the preference ratings and the mean frequency magnitudes are shown in Table 3. Correlations for 1M (-0.13), 2M (-0.35) and 3M (-0.32) were significant for 3M and large for 2M; (for $df = 51$, crit.(r) = 0.268 at $\alpha = 0.05$; crit.(r) = 0.348 at $\alpha = 0.01$). Irrelevant to the evaluation of the three filters, multiple (R) was also significant; $R = 0.39$, $F(3, 49) = 2.98$, $p = 0.04$.

TABLE 3. Correlations (r) in Study "V" between preference ratings and mean frequency magnitudes.

Validation				
r	Pref1	1M	2M	3M
1M	-0.13	1		
2M	-0.35	0.60	1	
3M	-0.32	0.15	0.53	1

Discussion

Correlations for filter (3M) remained significant despite the introduction of identifiable images in the stimuli set.

4. Concluding Analysis

Correlation (r), mean correlation, standard deviation of the mean, multiple correlation(R) and p-values for all studies are shown in Table 4. The

[3] See Table 4 in ___ under review by Environment and Planning B: Planning and Design, Pion: London.

correlations for filter (3M) were significant in study "V" and largely robust in the others. Filter (2M) was largely significant in both Study "S" and "V", (where identifiable stimuli were included), but did not perform well in C1 and C2. Filter (1M) performed poorly in all studies. Regardless of individual performances, multiple (*R*) values for the three filters were largely significant to preference in all studies.

TABLE 4. Correlation (*r*), mean correlation, standard deviation of the mean, multiple correlation(*R*) and p-values for all studies.

			Crit *r*		*r* value						
Study	*n*	*df*	α = 0.05	α = 0.01	1M	2M	3M	mean *r*	stdev	*R*	*p*
Selection	50.00	49.00	0.276	0.358	-0.22	-0.36	-0.55	-0.38	0.102	0.58	0.0003
Confirm1	20.00	19.00	0.433	0.549	0.03	-0.27	-0.59	-0.28	0.208	0.60	0.0639
Confirm2	20.00	19.00	0.433	0.549	-0.19	-0.29	-0.63	-0.37	0.070	0.65	0.029
Validation	53.00	52.00	0.268	0.348	-0.13	-0.35	-0.32	-0.27	0.159	0.39	0.0403

DISCUSSION

For the stimuli tested in this study, information extracted by filter (3M) was found to be largely correlated to aesthetic ratings. This is saying that (extracted at the scale of 0.35cycles/pixel) a low magnitude of frequencies is largely associated with preferred textures and high frequency magnitudes are largely associated with less preferred textures. The frequency magnitudes extracted at the scale of 0.18 cycles/ pixel, filter (2M) were significant, but not large and robust like those of (3M). And, those taken at 0.09 cycles/ pixel, (1M) were not significantly related to preference at all in this research.

Although only the (3M) setting was robust in terms of single correlation (r), the values for multiple (*R*) for (1M), (2M) and (3M) combined were large and robust across all studies. Nevertheless, this does not mean that filter settings (1M) and (2M) are reliable predictors of preference. The results do however indicate that the frequency characteristic of filter (3M) is likely to be a predictor of preference. More study needs to be done to understand preference perception in terms of 1) the standard deviation of the mean frequency magnitudes and 2) specific orientations and frequencies; these will be reported in subsequent papers.

It is suggested at this point that these results indicate homogeneity smoothness) exists in the preferred images and perhaps that structural grouping is present; however, more analysis must be conducted. Correlations did remain significant despite the introduction of identifiable stimuli in the last study; indicating that the identifiability of texture did not affect the relationship between preference and mean frequency magnitudes. In this, it is posited that specific frequencies do play a role in human preference despite cultural variables. Nevertheless, the relationship is not linear, and more work is needed to establish the characteristics of non-linearity present in (texture) preference perception. The relationship established in this research between specific frequency content and preference is consistent with Albrecht and Geisler's (1997) work on the cortex of primate monkeys; indicating that human beings are tuned to specific frequencies and orientations.

5. Experiment Methods

GABOR FILTER SETTINGS

Textural properties of images can be examined when they are represented digitally as a function of two variables (x_n, y_n) that assigns a gray-tone value to each pixel. As a result, the image is stored as a two-dimensional array resulting in a matrix of "elements" (pixel gray tone values) representing the spatial domain. The digital image becomes an input function for filtering. Simple statistics can then be obtained from the gray values in the filtered images by decomposing the original image into several filtered images using tuned 'channels'; each representative of specific spectral information.

A bank of filters is constructed for this project according to (Bovik, Clarke and Geisler, 1990; A.K. Jain, F. Farrokhnia, 1991). In order to obtain very low frequencies, the mean intensity over the entire image is set equal before applying the filters; done by removing the mean locally. The location of each filter (channel) on the frequency plane of a *150´ 150* pixel image input is determined by an orientation angle ***q*** and a central (radial) frequency *F*. For this project, ***q*** = 0*p*, *p*/4, *p*/2 and 3*p*/4, (0°, 45°, 90° and 135°)[4] and *F* = 0.08, 0.17, 0.35 cycles/pixel; that is, structure at the scale of 12, 25.5, 52.5 cycles/image width is extracted.[5] Each radial frequency is spaced one octave apart, guaranteeing that the pass band of the filter with the highest radial frequency falls inside the image array (Campbell, 1974). The width of each channel is given by a scaled bandwidth parameter, sigma (s), of a modulating Gaussian that varies inversely to the center frequency *F* (*U*, *V*). This Gaussian (description omitted) has a minor axis oriented at an angle ø from the *u*-axis (rotated axis), an aspect ratio 1/ ?, radial central frequency *F* = v(U^2 + V^2) in cycles/ image width, and an orientation *(?)* = $\tan^{-1}$ (*V/U*) in radians from the *u*-axis.

Figure 4 shows the impulse response components, real (a) and imaginary (b), of a Gabor filter. This can essentially be called the receptive field. The version (the Fourier domain) of the filtered image after it has been modified by the (MTF) is shown in Figure 5. This is a visual description of how many

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[4] Limiting the filter bank to four orientations is computationally efficient and has been considered sufficient for discriminating textures.

[5] An illustration of these settings are documented in ____________.

high and low frequencies occur in the image (globally). In this way it should be understood that the Fourier transform works at the global level, calculating all frequencies in all directions.

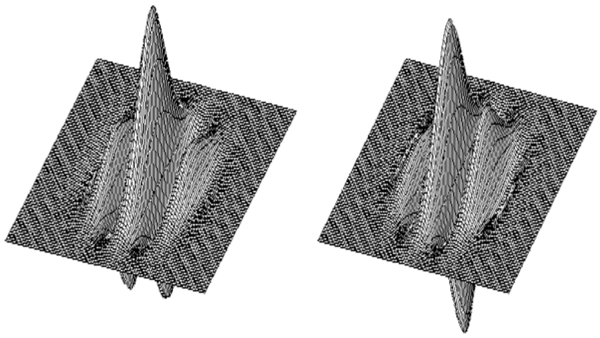


Figure 4. Impulse response. Real component (a) and imaginary component (b) of even symmetric Gabor filter (receptive field)

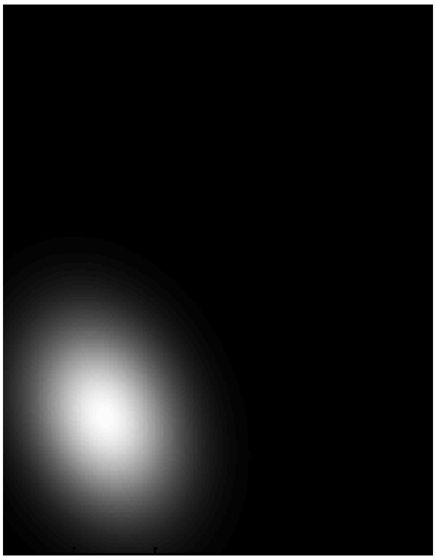


Figure 5. Fourier version of a Gabor filter. Low frequencies are gathered about the white center; the high frequencies span out from it.

In Gabor filtering, calculations are done in localities, and the magnitude of a band of frequencies at a certain orientation is extracted. Each filter comprised in the "bank" will give a different output. The output of each filter at each central frequency and orientation is shown, for example, in Figure 6. The frequency responses combine to create a Gabor filtered version (b) of the original image D051 (a) shown in Figure 7. The mean of the response value for each filter output is divided by the number of pixels (92752 to 92886) indicating the average magnitude of the frequencies present in the image. Dominant vertical edges in Fig.7, (a) will be expressed in the magnitude of output in the filter tuned to orientation (p/2) (or 90°) and low freq. (1v2). Hence this filter should be high in terms of output over all pixels; while the other eleven filters should give much lower outputs.

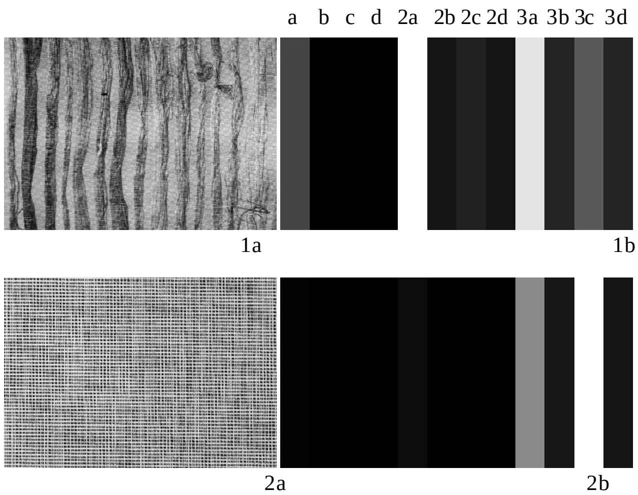
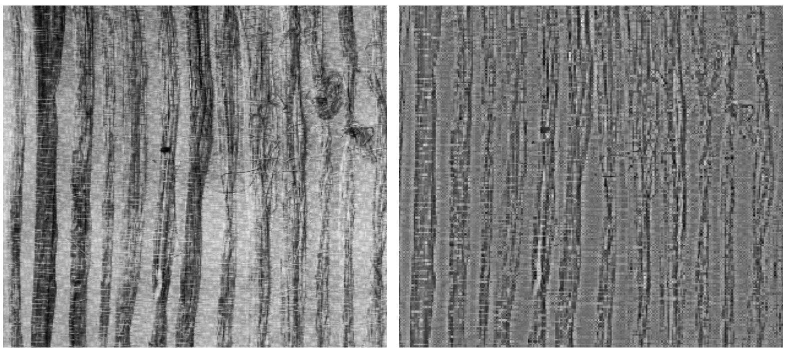


Figure 6. Filter bank response: mean global sum of frequency magnitudes (379.4) for input image 1 and (1051.2) for image 2 (Brodatz 1956).



(a) *(b)*

Figure 7. Original image (a) and reconstructed from 12 channel filter bank

5. Methods

316 psychology students participated in this research as means to partially fulfill a research requirement for an introductory psychology course; signing up by choice from an array of other experiments. The sign up sheet was coded with the very simple title, “Pictures.” They were generally young (18-

21), both males and females, and were members of diverse ethnic groups. Although there is the possibility that a student of design were included among the participants by chance, they were primarily considered unsophisticated in aesthetic study.

Each experimental session was held in a room 16'x 20' and consisted of 5 to 15 participants and each sat at a table aligned so as to allow full view of the projector screen. The distance any one participant sat from the screen was a minimum of 2.7m (9ft) and a maximum of 5.18m (17ft); a subtended visual angle from 36.9º to 20º.

Stimuli were obtained from Phil Brodatz (1956); scanned at 600 dpi, compressed to 150dpi, then sub-sampled every 4^h pixel (92752 to 92886 pixels) to increase filtering efficiency. The stimuli set was selected initially sorted to contain non-similar images of real world objects (textures) that were relatively non-identifiable in terms of the object originally photographed. This was in the attempt to control for cultural variables and adequately understand what physical features might be stimulating the mechanism responsible for preference (apart from the phenomenon of memory and association). Fifty images were selected under these criteria and used as the starter set.

Stimuli were presented with a standard LCD projector and laptop computer on a (1.8mW x 1.5mH) ($109.8m^2$) projector screen and was introduced at a rate of 3sec/image to familiarize the subjects with the stimuli and viewing pace. Each session lasted for approximately 25 min, consisted of presenting 20-53 stimuli in at least three random orders, and each participant made an aesthetic rating of each stimulus on a five-point scale.

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