Influence of Texture on Perceived Whiteness of Objects

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Abstract

The influence of surface texture on perceived whiteness (PW) of objects is examined. Ten woolen fabrics with different textures, knitted from the same yarn, were obtained and assessed for PW by a panel of observers previously. In this work we incorporated three factors, namely, roughness, directionality and density to represent image features of the scanned samples and determine whether a relationship between these features and PW is present. A correlation coefficient was used to examine the individual contribution of each factor to PW. A regression method was then developed to establish a model that related PW to these parameters. Results show that roughness is adversely related to PW while directionality and density are directly related to PW. Additional work is required to determine the role of these parameters on PW for a range of white substrates with different texture features. However, initial results indicate that the incorporating such parameters to indices of whiteness could potentially improve the correlation between visual and instrumental assessments of white objects. Results could also be potentially extended to colored objects.

Introduction

Whiteness is a perceived experience by the human observer, which is subjective, and strongly depends on illumination and surround conditions, among other factors. In addition, it has been established that inter-and intra-subject variability in the assessment of colored (including white) samples is relatively large [1], thus results can considerably vary among assessors. In addition, luminescence, due to the incorporation of fluorescent brightening agents, plays an important role in perceived witnesses of objects and thus potential variations in UV can contribute significantly to *PW* of objects [2].

Over the last several years, many studies have been carried out and a number of formulas have been proposed to determine the degree of whiteness of substrates. The first attempts exerted at describing whiteness were based on examining the role of lightness, yellowness or blueness [3-6]. The importance of the contribution of lightness to perceived whiteness was shown in the formula proposed by Hunter [6,7]. The ASTM-whiteness index is also defined using the tristimulus values of the object [8]. In 1981, CIE initiated extensive studies to resolve issues due to the excessive number of equations available for determination of whiteness and an equation, based on the results from Ganz [9-10], was proposed as the whiteness index.

Texture refers to properties that represent the surface features of an object. Approaches for analysis of texture can be categorized into statistical, structural and spectral methods. In the statistical method parameters such as Grey Level Co-occurrence Matrix (GLCM), and Markov random fields [11,12] are calculated based on information obtained from texture images. In structural approaches models based on the deterministic arrangement of textural elements are generated to describe texture characteristics [13]. The spectral methods separate the texture information in the frequency domain using transformation tools such as Fourier transforms [14].

A number of researchers have examined the relationship between texture and various colorimetric properties. Montag and Berns, for instance, studied the relationship between lightness (L*) and texture [15], while Xin, et. al [16] studied the effect of texture on color difference perception of samples. In a previous study [17,18] we investigated the effect of texture on the perception of lightness and whiteness of a set of textile samples. In this study we analyzed scanned images of those textured samples to elucidate the relationship, or lack thereof, of various texture features with perceived whiteness. The hypothesis tested was that increased surface texture reduces apparent whiteness.

Visual Assessment of Whiteness

Ten knitted woolen textures with different surface features were generated using the same bleached yarns and their PW was ranked by 25 naïve observers (13 F and 12M, mean age = 26). A rank of 10 was given to the most white and a rank of 1 to the least white sample under a simulated daylight illumination with a color temperature of 6500K and with an intensity of 1400 lux in the middle of a calibrated SPLIII viewing booth (X-Rite) [18]. For the analysis of results a weighting factor of 1 was assigned to rank 10 (most white) and 0.1 to rank 1 (least white) with other samples receiving a weighting factor between 0.1-1 according to rank with an interval of 0.1. The weighted probability rank for each texture was then calculated by summing up the products of rank and the corresponding weighting factors. The mean rank, weighted probability and colorimetric attributes are shown in Table 1.

Table 1. *The mean rank and weighted probability of woolen samples*

Textures	L^*	a^*	b^*	CIEWI	Mean Rank	Weighted Probability
Jersey Face	82.65	1.02	1.42	57.74	1	96.7
Jersey Back	82.47	1.00	1.31	56.76	2	77.5
2×3 Rib	82.07	1.31	1.51	56.52	3	67.8
Racking Effect	82.40	1.08	1.21	54.34	4	60.3
1×1 Rib	81.07	0.94	0.97	53.71	5	51.4
Bias Effect	82.59	1.10	1.29	52.71	6	50.1
Zigzag Effect	82.86	1.10	1.16	54.88	7	48.2
Half Cardigan Face	80.79	0.94	1.43	53.05	8	38.9
Full Cardigan	80.71	0.89	1.56	53.50	9	37.1
Half Cardigan Back	81.22	1.08	0.78	51.37	10	22.1

The 10 woolen knitted textures were scanned using an Epson XL10000 scanner at a resolution of a 300 dpi, and using no color management profile. All texture images were generated in Tiff format and are represented in Figure 1.

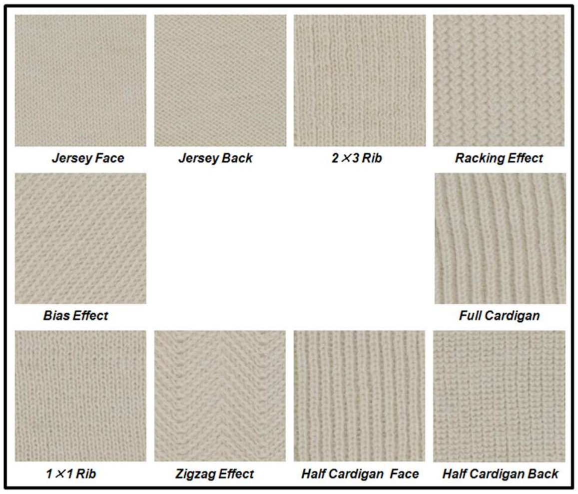

Figure 1. *Scanned images of the woolen knitted samples representing various textures examined in this study*

Features based on texture analysis

The human perception of texture may be identified with five characteristics [19], namely, regularity, understandability, roughness, directionality and density. In our study, regularity and understandability properties were ignored since for the purposes of the analysis samples here can be considered to be uniform. The relationship, therefore, between the *PW* and texture was examined using only three features: roughness, directionality and density.

Transformation to grey images

It has been indicated that the human visual system is composed of luminance and chrominance components [20, 21]. In our study, all samples were knitted using the same woolen yarns therefore the difference between samples, in terms of chrominance, was not significant. This was verified instrumentally using spectrophotometric measurements and the difference in chroma between samples was found to be less than 0.2 [18]. The scanned samples were converted to grey scale images, using Equation (1) [22], to isolate the effect of luminance on the perception of texture in this study.

$$f = 0.299R + 0.587G + 0.114B \quad (1)$$

where f is the value of the luminance channel in the YIQ color space, and R, G and B are pixel values for each scanned image in the RGB color space. Texture features of images were thus extracted from their corresponding grey-level images.

The Fourier transformation was then used to transform the images from a spatial domain to a frequency domain. The Fourier transformation is shown in Equation (2).

$$F(u,v) = \frac{1}{N \times M} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y) e^{-2\pi i\left(\frac{xu}{N}+\frac{yv}{M}\right)} \quad (2)$$

where (x, y) is the coordinate in the spatial domain, while (u, v) is the coordinate in the frequency domain, and f is the luminance of the grey-level images. Each image is in an $N \times M$ grid. $F(u,v)$ is the spectral value in the frequency corresponding to (u, v). When the image is a square, that is, $N=M$, the transformation is simplified to that shown in Equation (3):

$$F(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) e^{-2\pi i\left(\frac{xu+yv}{N}\right)} \quad (3)$$

Since Fourier transforms have the conjugate symmetry property, the lower frequency region where (u, v) was close to (0,0), was relocated to the center and the range of (u, v) was thus changed to $(-N/2, N/2)$. The spectral power of the entire image, $P(u, v)$ was thus calculated using Equation (4):

$$P(u, v) = |F(u, v)|^2 \quad (4)$$

Roughness

The GLCM (Grey Level Co-occurrence Matrix) has been used to describe the homogeneity of samples and assess the roughness of a texture [19]. However, this method was not suitable in this study since textures contained low homogeneity. In other words, the GLCM and image homogeneity are significantly changed when the distance and the direction between the co-occurrence points are altered. In our study the texton size and texture directions among samples are quite different, as shown in Figure 1, and thus the homogeneity derived from the GLCM method could not be used to compare their roughness.

Nonetheless, according to the GLCM method, two factors influence the roughness property, a change in: frequency, or scope. These two factors can be separately represented by the frequency and power of the image spectrum using a Fourier transform. The roughness of a texture can thus be described as a sum of the spectral power of the image, using appropriate weighting ratios based on its frequency.

In addition, in the visual system, a frequency response of a linear, shift-invariant system is composed of a magnitude response and a phase response. The magnitude response is called the modulation transform function (MTF), which can be used to illustrate the visual sensitivity of different frequency signals. A model for the MTF is given by the radially symmetric function, shown in Equation (5) [23]:

$$H(\omega) = A\left[\alpha + \frac{\omega}{\omega_o}\right] \exp[-\left(\frac{\omega}{\omega_o}\right)^{\beta}] \quad (5)$$

where ω is the circular frequency measured in cycles per degree, and can be transformed to cycles per mm. In this case in Equation (5), $A = 2.5$, $\alpha = 0.0192$, $\omega_0 = 8.772$, and $\beta = 1.1$.

The roughness of the scanned textures, R, was calculated using Equation (6). Results are shown in Table 2.

$$R = \int P(u,v) \cdot H(u,v)\, du\, dv \quad (6)$$

Table 2. Roughness of scanned images.

Textures	Roughness
Jersey Face	74.64
Jersey Back	77.22
2×3 Rib	107.24
Racking Effect	80.91
1×1 Rib	130.13
Bias Effect	80.15
Zigzag Effect	77.09
Half Cardigan Face	142.92
Full Cardigan	112.68
Half Cardigan Back	121.79

Samples in Table 2 are listed from the most white (Jersey Face) to the least white, based on the mean whiteness ranks obtained previously [17,18]. While this trend is not general, it can be seen that samples perceived as whiter, such as Jersey face and Jersey back, have lower roughness compared to those perceived as less white, such as the Half and Full Cardigan samples. This indicates an inverse relationship between roughness and *PW*.

Directionality

Edges have a significant influence on visual perception of images [19]. Directionality is defined as the main orientation of image edges in different directions of an image.

The line-likeness and orientation of edges are used to characterize the directionality of a texture, and the directional co-occurrence matrix (DCM) is used to calculate the line-likeness in an image as shown in Equation (7):

$$F_{dir} = \sum_{j}^{n}\sum_{j}^{n} P_{Dd}(i,j) \times cos|\,(i-j)\cdot\frac{2\pi}{n}| \,/ \sum_{i}^{n}\sum_{j}^{n} P_{Dd}\,(i,j) \tag{7}$$

where P_{Dd} is the n × n local directional co-occurrence matrix of points at distance *d*. This matrix is defined as the relative frequency with which two neighboring cells are separated by a distance *d* along the edge direction occurring on the image. Variables *i* and *j* are the direction codes in matrix P_{Dd}.

The disadvantage of the DCM method, however, is that only 8 directions can be used to depict the directionality of an image. With respect to the Fourier transform, a texture with a directionality angle of θ will have a high value of $P(u, v)$ in a perpendicular direction (90°+θ). The histogram of angular spectrum power can be used to describe the direction distribution of a texture [19].

The *A* parameter shown in Equation (5) is ranged from 0º-179º because of the conjugate symmetry property of Fourier transform. Angles out of the [0º, 179º] range are also represented by the conjugate angle due to the conjugate symmetry. The angular Fourier spectral power is calculated using Equation (8) [19]:

$$P(A) = \sum_{\theta=A} P(r,\theta) \qquad (A = 0^o, 1^o, 2^o \ldots\ldots 179^o) \tag{8}$$

where *A* is the angle in the Fourier spectrum, and $P(A)$ is the sum of the spectral power in direction *A*.

The directionality of a texture is a relative parameter to depict the line-likeness property. The angular spectrum power is normalized as shown in Equation (9):

$$W(a) = \frac{P(A)}{\sum_{\alpha=0^o}^{179^o} P(A)} \tag{9}$$

Assuming that the angle α has the highest probability (maximum *W*), Equation (10) is obtained by combining Equations (8), and (9) with Equation (7):

$$Dir = \sum_{\theta} w(\theta) \times \cos|(\theta - \alpha)| \tag{10}$$

where *Dir* is the directionality of a texture and α is the main orientation of the texture.

The directionality of the textures in this study was calculated using Equation (10) and the results are shown in Table 3.

***Table 3.** Directionality of the samples tested in this study.*

Textures	*Dir*
Jersey Face	0.80
Jersey Back	0.70
2×3 Rib	0.82
Racking Effect	0.71
1×1 Rib	0.82
Bias Effect	0.84
Zigzag Effect	0.61
Half Cardigan Face	0.86
Full Cardigan	0.90
Half Cardigan Back	0.65

The directionality feature is used to describe the line-likeness properties of a texture, and the directionality value close to 1 indicates that a texture is more uniform. The Zigzag Effect, Half Cardigan Back, and Jersey Back textured samples have lower directionality values which mean the main orientation of edges in these textures (or their directionality) is more varied.

Density

The perceived density of a texture refers to the density distribution of a texture in visual assessments [19]. Humans are more sensitive to variations in edges or regions of interest (ROI), e.g. color change. The texture originated from various textons can be regarded as the combination of different edges. The density of various edges of an image can be used to represent the density of a texture. The density of a texture is determined by the ratio between the pixel number of the extracted edges and the pixel number of the whole texture as shown in Equation (11) [19]:

$$Den = N_{edges} \,/\, N_{img} \tag{11}$$

where *Den* is the density of a texture, N_{edges} is the pixel numbers of the extracted edges of a texture, and N_{img} is the number of pixels of a texture.

The Density of each scanned texture, calculated based on Equation (11), is shown in Table 4.

***Table 4.** Density of the scanned textures.*

Textures	*Den*
Jersey Face	0.26
Jersey Back	0.26
2×3 Rib	0.22
Racking Effect	0.21
1×1 Rib	0.22
Bias Effect	0.19
Zigzag Effect	0.20
Half Cardigan Face	0.17
Full Cardigan	0.18
Half Cardigan Back	0.20

The density of the images decreases from the most white samples to the lesser white samples, which means the number of the edge points of the whiter samples is larger than that of the less white samples. The increase in the density of a texture indicates edges in the image are compactly distributed. In other words, the texture visually appears to be more condensed. The density property of a texture seems to have a positive effect on *PW* of tested samples.

The effect of texture elements on *PW*

The *PW* of samples examined in this study was affected by three factors: roughness, directionality and density of the corresponding grey-level images. The analysis of the influence of these attributes on the *PW* was carried out using two approaches: examination of the effect of the individual factor on *PW*; and the effect of the combined features on *PW*. These are briefly described in the following sections.

The influence of individual factors on the perceived whiteness

The relationship between the *PW* and each of the stated texture features is shown, individually, in Figures 2- 4.

The roughness factor has a negative role on *PW*, and increasing roughness decreases *PW* of the object as shown in Figure 2. However, it should be noted that the R^2 is only 0.383 while the correlation coefficient (r) was -0.619. The negative correlation coefficient supports the inverse role of roughness on *PW* while the value itself implies that the individual differences in *PW* are not accidental and are related to variability in roughness. It should be pointed out however, that the number of samples tested in this study was limited and thus additional results would likely be needed to draw firm conclusions.

The effect of directionality on perceived whiteness of samples was not clear as shown in Figure 3. The trend line is nearly horizontal with R^2 = 0.002, and the correlation coefficient was only 0.044 (See Figure 3). Directionality is a relative parameter thus it seems appropriate to examine the effect of directionality in combination with other texture features.

Density has a positive effect on *PW* of tested samples with R^2 = 0.723, and r = 0.850. Results indicate that density has the most important role on *PW* of samples (See Figure 4). Increasing density increases the edges in a certain area, and thus the texture appears more compact and condensed.

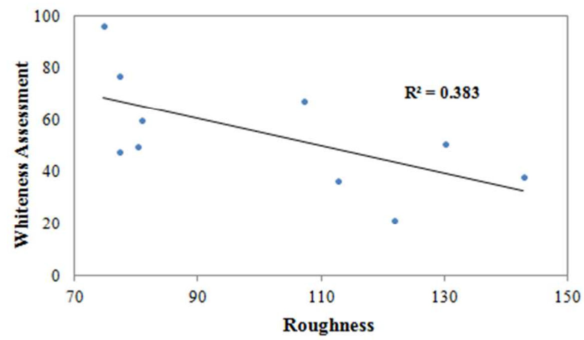

***Figure 2**. The relationship between Roughness and PW*

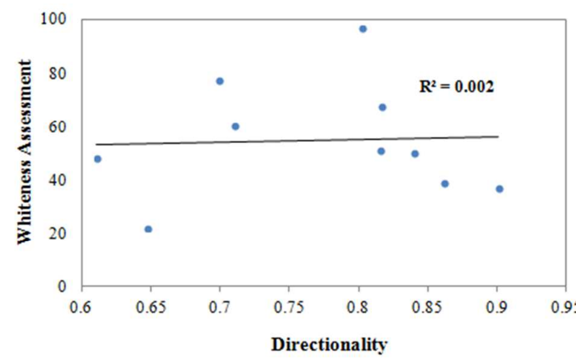

***Figure 3.** The relationship between Directionality and PW*

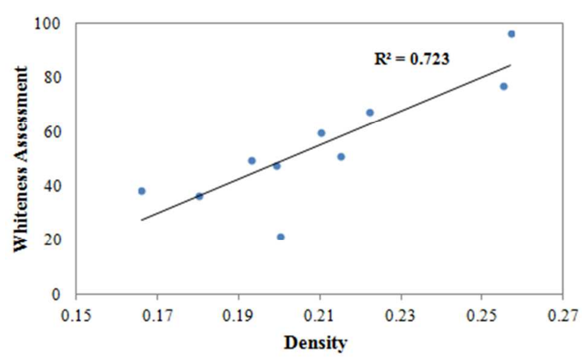

***Figure 4.** The relationship between Density and PW*

The influence of combined factors on the perceived whiteness

As indicated directionality is a relative parameter that represents the directional distribution of a texture and the parameter (*Dir*) is obtained from the normalized spectral power angular distribution of the image. On the other hand, Roughness (*R*) is an absolute parameter, which is related to 'power' perception of a texture based on variations in frequency. In order to determine the potential role of directionality on *PW*, directionality was multiplied by roughness to generate a combined factor denoted 'directional power'. The role of 'directional power' on *PW* was considered to be additive.

All texture features were combined and a regression analysis was carried out to determine the relationship among parameters. The results of the regression are shown in Table 5. Results were normalized to remove potential induced biases.

Table 5. *Results of the regression analysis*

Textures	*R*	*R × Dir*	*Den*	*PW*
Jersey Face	74.64	59.80	0.26	99.7
Jersey Back	77.22	53.97	0.26	77.5
2×3 Rib	107.24	87.55	0.22	67.8
Racking Effect	80.90	57.45	0.11	60.3
1×1 Rib	130.13	106.08	0.22	51.4
Bias Effect	80.15	67.26	0.19	50.1
Zigzag Effect	77.09	47.08	0.20	48.2
Half Cardigan Face	142.92	123.00	0.17	38.9
Full Cardigan	112.68	101.52	0.18	37.1
Half Cardigan Back	121.79	78.83	0.20	22.1

In Table 5, *R, R* $\times$ *Dir* and *Den* were regarded as independent variables, and *PW* was considered to be the dependent variable. The data was simulated using Regression method with Matlab and the model shown in Equation (12) was obtained.

$$PW = c - 1.02 \cdot R + 0.94 \cdot (R \cdot Dir) + 585.58 \cdot Den \tag{12}$$

where *c* is constant.

The F values and R^2, to assess the significance of parameters for this model are 19.13, < 0.01 and 0.91, respectively which indicates this model is reliable. The P-value of each independent variable is examined since each variable is not normalized in the same magnitude. All the P-values obtained were smaller than 0.02, which means each of the independent variables plays an important role in the model.

The coefficient of 'directional power' (*R* $\times$ *Dir*) is positive, which indicates 'directional power' is directly related to *PW*, and increasing 'directional power' will increase the perceived whiteness. Directionality is a parameter to assess the line-likeness property within the image, and a directionality value close to 1 indicates the texture is more uniform. Increasing the directional power results in the increase of the texture uniformity, which is shown to improve its perceived whiteness.

Conclusions

The influence of texture on the *PW* of a set of objects was investigated in this study. Ten woolen samples with different textures, representing common surface patterns in textiles were developed using the same yarns. Knitted samples were then assessed by a panel of color normal observers. Visual assessment results were obtained and the individual as well as combined effect of three factors, namely, roughness, directionality and density on *PW* was separately examined using simulation and regression methods.

It was shown that roughness feature of a texture has a negative effect on *PW*, increasing roughness resulted in decreasing perceived whiteness. Directionality is a parameter that is used to define the line-likeness property of a texture and thus the uniformity of the texture. It was found that increasing uniformity improved *PW*. Density is related to the compactness of a texture and was also found to have a positive effect on *PW*.

Using regression analysis an initial model was developed based on the relationship between the three texture features and *PW*. While promising, the model is limited due to the limited number of textures examined. Extended studies involving additional samples with a wider range of surface patterns could result in development of similar improved models that would elucidate the relationship between perceived and measured whiteness of textured objects.

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