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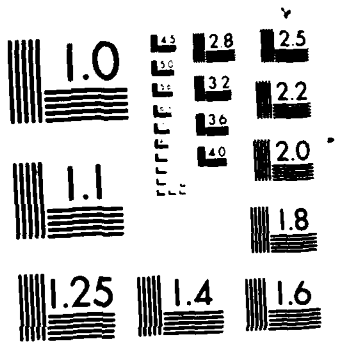

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C.J. Woodruff

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ABSTRACT

The role of camouflage patterns is briefly described, and the need for quantification of visual texture in this context developed. A procedure is described for developing a perceptually-based measure of the similarity of foliage textures. The procedure is based on first determining the perceptual dimensions underlying judgements of texture similarity, followed by the derivation of mathematical descriptors of these dimensions, based on digital encodings of textures.

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CONTENTS

A PROPOSED METHODOLOGY FOR THE SPATIAL CHARACTERISATION OF FOLIAGE BACKGROUNDS

1. INTRODUCTION

The procedure outlined in the following Note is proposed as a means of quantifying visual texture perception of images of natural foliage. The work is in response to Army Task ARM 81/139 (subsequently replaced by ARM 84/169), which required a methodology for such characterisation to be developed. Current work is oriented towards ground-based observation of natural foliage, with the use of black-and-white photographic negatives as the primary image source. Emphasis in the work will be placed on the relation between visual perception of projected images of foliage scenery and digital encodings of the corresponding images.

In outlining the procedure through sections 2 and 3, colour is used in its general sense, subsuming monochromatic images as a subset of colour images, and texture is likewise treated as arising from both brightness and chroma variations. Although the published literature on texture deals only with monochromatic systems, the concept cannot reasonably be restricted to such images, and hence, where it is reasonable to do so here, the more general sense of texture is used. However, in elaborating on mathematical descriptors of texture in section 4, discussion is restricted to monochromatic textures because of both limitations in the available hardware, and the assumed greater simplicity of working in only the brightness dimension of colour. It is, however, assumed that analogous procedures could be applied to full colour textures - though at some considerably greater degree of complexity.

The widespread trend in military camouflage towards patterning of nets, uniforms, vehicles and aircraft has relied on patterns developed almost entirely by heuristic methods supported by limited post facto evaluation. By quantifying visual texture in a way related to the perception of texture differences, a basis for more systematic pattern development will be provided. In particular the problem of determining a compromise pattern over a range of foliage textures may be systematically approached and the basis for any recommendation for future camouflage patterning more fully justified. In addition, as the need for wider spectral range countermeasures arises, a fuller understanding of patterning in non-visual spectral ranges may be required. A further consideration in developing a quantification of visual texture based on human perception is its potential use in synthetic texture generation, both for training simulators and for preprocessing of displayed images produced by future generations of surveillance instruments.

Patterning can be described as the superposing on an object of fine detail colour variations about a colorimetric mean, with an analogous definition for non-visual spectral images. In camouflage patterning the intended function is to produce colour variations within the target perimeter which

(i) are colorimetrically and spatially consistent with those in the backgrounds within which the target operates;

or

(ii) reduce the detectability of known visual cues, such as horizontal edges and shadows;

or both (i) and (ii) above.

The first function relates closely to patterning for variable shape targets such as nets and uniforms, and its application is detailed in Skinner and Jenkins [1]. The second is more appropriate for fixed shape targets such as aircraft, ships, vehicles, and buildings. Beckwith [2] describes an approach to vehicle patterning based primarily on this latter function.

2. QUANTIFICATION OF TEXTURE

The concept of texture* is a psychophysical construct used to describe those spatial variations in colour which give rise to a perceived local uniformity despite being individually resolvable, or nearly so. Typically such variations are rapid by comparison with changes in features of the image which are perceived in some structural relationship to each other. For example, a scene showing a section of a golf course in which stand isolated trees would have a background texture of grass, with trees and bunkers being some of the features.

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* I will not attempt here a rigorous delineation between textures and features, but suggest that numerosity of resolvable elements is a critical feature [11 - 13], as well as angular subtense of resolvable elements [14], and edge contrast.

Texture quantification, therefore, requires at least a measure of the (spatial) rapidity and extent of colour variation from the local mean, and may also need measures of spatial correlation, or other structural features of the variation. Various descriptors have appeared in the image processing literature, some based on Fourier analysis [3], others on stochastic processes [4-6], and others on structural analysis approaches [7-8]. These descriptors have often arisen from an intuitive approach to specifying those aspects of texture which are perceptually significant. From this approach, concepts such as coarseness, busyness, regularity, line-likeness, etc. have arisen.

A significant attempt to systematize the relationship between perception of texture and mathematical descriptors was presented by Tamura et al. [9], who used a set of textures from the Brodatz album [10]. They verbally defined six characteristics of texture, then presented all possible pairwise combinations of the textures to the subjects, who were to specify which of the pair was higher on each of the characteristics described. These characteristics were labelled coarseness, contrast, directionality, line-likeness, regularity, and roughness. A set of mathematical descriptors was then developed which were considered appropriate for quantifying the characteristics described. For these measures the resulting rank correlation between the mathematical descriptors and the averaged subjective ratings on that characteristic ranged from 0.615 to 0.904. There was considerable intercorrelation of the various dimensions in both the subjective and the mathematical measures.

These results of Tamura et al. provide justification for the use of terms such as coarseness, directionality, etc. However they do not provide a basis for the development of a psychophysics of texture having a value similar to that of the psychophysics of colour. This is because the dimensions used are strongly correlated and no attempt has been made to search for a better definition of the perceptual dimensions. Further, there is no evidence that estimates of texture difference made along individual specified dimensions are valid when judging overall texture differences simultaneously along all available dimensions. Statistical techniques such as factor analysis, cluster analysis and multidimensional scaling allow one to search systematically for such perceptual dimensions.

A partial validation of the use of multidimensional scaling in extracting the perceptual dimensions of colour was provided by Wright [15], who showed that perceptual judgements on different coloured equally luminous reflectance tiles gave results consistent with two major dimensions of colour difference, these two dimensions corresponding to hue and saturation. More recently Sokolov et al. [16] have used multidimensional scaling to extract three dimensions underlying the perception of colour. These authors found the same underlying structure for both a colour designation technique and a paired comparison technique. Harvey and Gervais [17], in a study of texture discrimination using synthetic one dimensional textures, used multidimensional scaling to show that texture discrimination was well defined by three perceptual dimensions corresponding to three spatial frequency bands. Thus multidimensional scaling appears to be an appropriate tool to use in determining the dimensions of perceptual spaces.

The method proposed here makes no assumptions about which aspects of texture might be important. Rather it uses judgements regarding texture dissimilarity to provide proximity (distance) measures on a set of textures, from which an n-dimensional configuration of points - each point representing a texture - is determined, this configuration being consistent with their judged proximities. Following the determination of the dimensions underlying the perception of texture differences, mathematical descriptors can be developed for each dimension.

3. MEASUREMENT OF PERCEIVED TEXTURE SIMILARITY

Suppose a set of N texture samples representing the textures of interest is selected. A measure of judged proximity of these textures is required. This is obtained using the method of paired comparisons, the comparisons in this case being of texture differences. Subjects are shown three textures side-by-side, with the left and right hand textures being judged for degree of similarity to the central texture (see Fig. 1). Thus two texture differences are being compared - between the left texture and central texture, and between the right texture and central texture. Each texture is placed in the centre and all possible pairs of textures are compared to the central texture. Because the textures are from natural foliage scenes some non-uniformities exist within a particular texture which may lead to an assymetric assessment of similarity according to whether it is to the left or right. Hence each texture appears on both sides of the central texture.

Subjects are required to judge which of the two outer textures is more similar to the central one, with the option of judged equality. Scoring is -1, 0, +1 according to whether the judgement is "left-hand", "equally similar", or "right-hand" respectively. Given N textures, and allowing for identical textures to be placed simultaneously in two or three locations, there are N^3 judgements to be made. From these an N x N dissimilarity matrix for the textures can be derived, as described in the Appendix.

The exposure duration for a single comparison set of three textures is chosen by consideration of the requirements of the comparison task. It is assumed that a series of fixations is made, with at least one fixation on each of the outer two textures and two on the central texture. Based on reaction latencies obtained in other texture discrimination experiments [11], and also in studies of visual comparison processes [18], a time of approximately 0.5s per fixation is estimated for this task. Any longer exposure would probably enhance individual differences in processing between what Cunningham et al. [18] describe as holistic versus analytic processors. It is the holistic processing which is of interest here. Hence an exposure time of 2.0s is proposed for each comparison set.

In order to obtain a useful relation between the digital image and results from an experiment of the type described here, it is imperative that the function mapping the grey levels onto perceived image brightness be well-defined. Probably the most suitable procedure is to determine the functional relation between grey levels and display brightness for the specific hardware used, and then transform the raw image prior to display such that equal grey level differences give equal brightness differences for all grey levels and field positions used. Mathematical descriptors can then be derived from grey levels of the (unmodified) raw image. The image modification matrix is obviously dependent on the particular system used, but any results obtained will be system-independent.

4. MATHEMATICAL DESCRIPTORS OF TEXTURE SIMILARITY

In this and the following sections attention is confined to monochromatic textures, though there is a need for future work to develop procedures applicable to full colour images.

Digitisation of (monochrome) images recorded on photographic film normally involves quantizing the transmittance of a matrix of small regions of the photographic image into equally-spaced steps. This quantization is commonly done by a special purpose TV camera, or - for higher spatial resolution - by a rotating drum scanner. The result is to produce a matrix of transmittance values with arbitrary zero and scale (determined, for instance, by the "black level" and "gain" settings of a TV camera). Commonly the matrix will be square of size 512 x 512 with matrix elements lying in the range 0 to 255, corresponding to an 8 bit binary representation. Each picture element sampled is called a pixel, and each matrix element representing the luminance of a pixel is called a grey level.

Suppose a segment of "uniform" texture is digitised and the discrete two-dimensional Fourier transform of the the matrix of grey levels found. This gives a set of (generally complex) values, F_{ij}, $i = 0,1,\ldots M-1$, $j = 0,1,\ldots M-1$ of the spatial frequency function. A subset of these values $\{F_{ml}\}$ is selected, from which a summary measure, $S(F,m)$, of texture is derived such that $S(F,m)$ correlates strongly with the mth dimension of perceived texture similarity as determined by the earlier psychophysical experiment. The simplest form of $S(F,m)$ is a linear sum

$$S(F,m) = \sum_{l=1}^{L} a_{ml} F_{ml}$$

where the a_{ml} are weighting coefficients. $S(F,m)$ is an example of a mathematical descriptor of texture, in this particular case being a Fourier-based descriptor for the mth perceptual dimension. Corresponding descriptors for the other dimensions, previously determined in the psychophysical experiment, are also derived, thus producing a set of texture measures along the known perceptual dimensions. Any texture is then located in texture space by the set of values $\{S(F,i),\ i=1,2,\ldots D\}$ where D is the number of dimensions in texture-perception space. The similarity of two textures is then determined by simply calculating the distance between them, using the metric specified in the multidimensional scaling analysis.

The previous paragraph used Fourier-based descriptors as an example of one type of mathematical descriptor. Haralick [19] has proposed the use of co-occurrence (or spatial grey level dependence) matrices for texture analysis. A co-occurrence matrix for a given vector displacement, **d**, has elements C_{ij} such that C_{ij} is the observed relative frequency that, for a pixel of grey level i, the pixel at a displacement $\pm$ **d** is of grey level j. A set of descriptors $\{S_{Ci}\}$ based on co-occurrence matrices could be sought. Laws [5] has proposed a set of pixel operators which have proven to be powerful discriminators of texture [20], and a set of texture descriptors based on these may also be valuable.

In searching for appropriate descriptors, both the known characteristics of human perception of texture and the limitations of the image acquisition and display system need to be considered. Julesz [21], and Julesz et al. [22] have postulated that, to a very considerable extent, humans are unable to differentiate textures differing only in their third and higher order statistics, but can spontaneously discriminate those differing in their second-order statistics. It is appropriate therefore to concentrate on descriptors which are based on second-order statistics. Descriptors mentioned in the previous paragraph all fall within this category. Wilson and Bergen [23], and Bergen et al. [24] presented evidence for human static visual perception being based on a set of four spatial frequency bands whose frequency varies with retinal eccentricity. This approach was subsequently developed by Marr [25], and also investigated by Harvey and Gervais [17] who found supporting evidence from studies of the perception of one-dimensional textures synthesized from sinusoids having frequencies in various of these bands. Caelli [26] has developed procedures for investigating two-dimensional textures, and presented evidence for orientationally-selective channels having a variance, σ, which decreases with frequency, ω, according to $\sigma(\omega) = 5 - 0.125\,\omega$. Qualitatively similar results were obtained by Phillips and Wilson [27], though they found a more rapid decrease in half-width with spatial frequency.

All of the above results indicate that a reasonably limited set of quantities based on spacing of pixels and selected orientations can be expected to describe the dimensions of texture perception of natural textures.

In deriving a particular descriptor, the selection of weighting factors, a_{ml}, is based on maximizing the correlation between judged texture similarity dimension and the calculated value of the corresponding texture descriptor. This maximization can be achieved using the statistical technique of canonical correlation.

5. CONCLUSION

The methodology as outlined is applicable to monochromatic, continuous-tone natural textures presented in two dimensions. With appropriate development of descriptors it should be applicable to coloured natural textures.

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APPENDIX

DERIVATION OF A DISSIMILARITY MATRIX FOR TEXTURES

Suppose N = 5 textures are to be judged for similarity. For each subject a matrix of judgements is produced for each reference texture. For example, with texture 4 as the reference (central) sample, the matrix could be as follows:-

		Right hand texture number					row sums
		1	2	3	4	5	
Left	1	0	−1	1	1	1	2
hand	2	1	0	1	1	1	4
texture	3	−1	−1	0	1	−1	−2
number	4	−1	−1	−1	0	−1	−4
	5	0	−1	−1	1	0	−1
Column sums		−1	−4	0	4	0	

It should be noted that the table indicates two apparently inconsistent comparisons:-

(i) when the judgement involves textures 3 and 5 simultaneously whichever is on the left appears more similar to texture 4;

(ii) when textures 5 and 1 appear simultaneously no discrimination is made when 5 is on the left, but when it is on the right it is judged more similar to 4 than is texture 1.

Clearly, the more closely a texture resembles the central texture, the more the corresponding row will have negative numbers and the corresponding column will have positive numbers. Hence, if we define a function for each non-central texture j (j = 1,2,...N) as the row j sum minus the column j sum, this will, given perfect consistency in judgement, range from −2(N−1) for the most similar texture (which is the same as the central texture), to 2(N−1) for the least similar. In our example this gives

Texture number	1	2	3	4	5
	3	8	−2	−8	−1

Subtracting the most negative value from all gives a dissimilarity score which is zero for the most similar texture, with larger values indicating less similar textures. These values provide one column in an individual's dissimilarity matrix. By repeating the process for all reference textures a complete dissimilarity matrix is obtained for each subject. The average matrix for each subject or across all subjects may provide the input to a multidimensional scaling program. It is expected that the input matrix would have zero or near-zero diagonal elements, but it is not expected that it should be symmetrical about the diagonal, since all columns are individually scaled. However, multidimensional analysis can be carried out using only in-column comparisons.

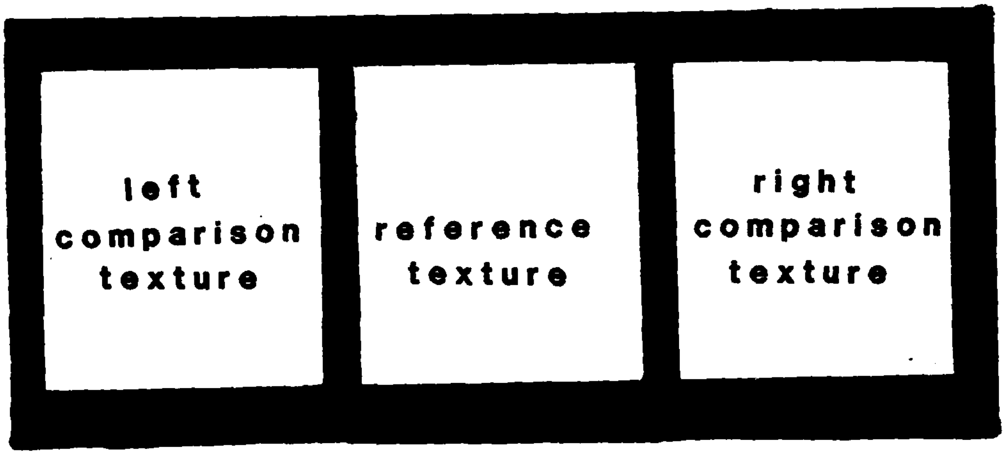

FIGURE 1 Presentation format for texture similarity judgements.